Equity in the Time Series, Part 2

15.433 Financial Markets

October 3 & 5, 2017

This Version: September 26, 2017
Outline

- Volatility models and market risk measurement.
- Estimating volatility using financial time series:
  - SMA: simple moving average model (traditional approach).
  - EWMA: exponentially weighted moving average model (RiskMetrics).
  - ARCH and GARCH models (Nobel Prize).
- EWMA for covariances and correlations.
- Portfolio volatility and Value-at-Risk.
What have we learned about the aggregate stock market?

- It is pervasive, the single most important risk factor in the equity world.
- It yields a positive risk premium, but the risk premium is difficult to measure with precision because of
  - the “high” level of stock market volatility
  - and the limited length of the historical data.
- There is some evidence that the expected returns are time varying. The autocorrelation of the aggregate stock returns is slightly positive, and the dividend-to-price ratio has some predictability for future stock returns.
- Overall, only a small portion of future stock returns can be predicted (low R-squared’s), and much of the uncertainty is unpredictable.
The volatility of the aggregate stock market

- Historical data can be used to measure volatility with much better precision. Between risk and return, risk is something we can collect more information about.

- In fact, we can learn about market volatility not only from the historical stock market data (backward looking), but also from derivatives prices (forward looking).

- Academics have made much progress in both directions, and practitioners have adopted many of the ideas developed by academics.

- We will study three volatility estimators:
  - SMA: simple moving average model (traditional approach).
  - EWMA: exponentially weighted moving average model (RiskMetrics).
  - ARCH and GARCH models (Nobel Prize).
The importance of measuring market volatility

- Portfolio managers performing optimal asset allocation.
- Risk managers assessing portfolio risk (e.g., Value-at-Risk).
- Derivatives investors trading non-linear contracts with values linked directly to market volatility.
- Increasingly, the level of market volatility (e.g., VIX) has become a market indicator ("the fear gauge") watched closely by almost all institutional investors, including those who are not trading directly in the U.S. equity or U.S. equity derivatives markets.
Modern Finance

Portfolio Theory (Markowitz)
Option Pricing Theory (Black, Scholes, Merton)
Two-Fund Separation (Tobin)
CAPM (Sharpe)
Behavior of Securities Prices (Samuelson)
First Major Study of Mutual Funds (Jensen)
Investments and Capital Structure (Modigliani and Miller)
Efficient Markets Hypothesis (Fama)
Index Mutual Funds (Bogle)
Birth of Index Funds (McQuown)
First US Options Exchange, CBOE
RIse of Junk Bonds
Mortgage-Backed Securities
Index Futures
S&L Bailout
Collapse of Junk Bonds
Crash
OTC Derivatives (e.g. interest-rate swaps)
Credit Derivatives (e.g. CDS)
Large Derivatives Losses
Peak
Bottom
Summer 2000
Summer 2002
Summer 2005
Summer 2006
Summer 2007
Summer 2008
Summer 2009
Summer 2011
Summer 2013

Fall 2017
Jun Pan, MIT Sloan
The Evolution of an Investment Bank

1869

Marcus Goldman
Buy/Sell Commercial Papers

1870

Firm Capital: $100K

1880-1882

Goldman Sachs
Trading Corporation

1890-1900

Sears IPO
Lead Underwriter with Lehman

1907-1920

Sidney Weinberg takes over (builds Investment Banking Business)

1928

Crash

1930

Proliferation of Investment Trusts;
Cheap & easy credit fuels leverage

1941-1947

Lead Underwriter of Ford IPO

1947-1953

Gus Levy takes over
(builds risk arbitrage business)

1956

Penn Central Bankruptcy
Commercial Paper Scandal

1969

Whitehead and Weinberg
14 business principles
“Our clients’ interests always come first”

1970

Acquired J. Aron
(commodity)

1976

Hires from Salomon
(fixed income)

1980-2006

Firm-wide risk management

1986

Freeman, head of risk arbitrage
arrested for insider trading

1990

Rubin and Friedman

1994

Huge trading losses in FICC

1997

Record year in trading profits

2006

CEO Blankfein
Acquired SLK
(NYSE specialist)

2008

IPO; CEO Paulson

2009

LTCM crisis
IPO withdrawn

1930-40's

Gov’t antitrust case against 17 banks

1947-53

Sidney Weinberg takes over (builds Investment Banking Business)

1969-1976

Time of very little business and virtually no profits

1987

LTCM crisis
IPO withdrawn

1997

Record year in trading profits

2008

LTCM crisis
IPO withdrawn

1990

Rubin and Friedman

1994

Huge trading losses in FICC

1997

Record year in trading profits

2006

CEO Blankfein
Acquired SLK
(NYSE specialist)

2008

IPO; CEO Paulson
Some losses on derivatives positions by non-financial corporations in mid-1990s

Orange County: $1.7 billion, leverage (reverse repos) and structured notes

Showa Shell Sekiyu: $1.6 billion, currency derivatives

Metallgesellschaft: $1.3 billion, oil futures

Barings: $1 billion, equity and interest rate futures

Codelco: $200 million, metal derivatives

Proctor & Gamble: $157 million, leveraged currency swaps

Air Products & Chemicals: $113 million, leveraged interest rate and currency swaps

Dell Computer: $35 million, leveraged interest rate swaps

Louisiana State Retirees: $25 million, IOs/POs

Arco Employees Savings: $22 million, money market derivatives

Gibson Greetings: $20 million, leveraged interest rate swaps

Mead: $12 million, leveraged interest rate swaps
Measuring Market Risk

• By the early 1990s, the increasing activity in securitization and the increasing complexity in the financial instruments made the trading books of many investment banks too complex and diverse for the chief executives to understand the overall risk of their firms.

• Market risk management tools such as Value-at-Risk are ways to aggregate the firm-wide risk to a set of numbers that can be easily communicated to the chief executives. By the mid-1990s, most Wall Street firms have developed risk measurement into a firm-wide system.

• Daily estimates of market volatility, along with correlations across financial assets, constitute the key inputs to Value-at-Risk. JP Morgan’s RiskMetrics uses exponentially weighted moving average (EWMA) model to estimate the volatilities and correlations of over 480 financial time series in order to construct a variance-covariance matrix of 480x480.
### Table 9.5

**Equity indices: sources**

<table>
<thead>
<tr>
<th>Market</th>
<th>Exchange</th>
<th>Index Name</th>
<th>Weighting</th>
<th>% Mkt. cap.</th>
<th>Time, U.S. EST</th>
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<td>Australian Stock Exchange</td>
<td>All Ordinaries</td>
<td>MC</td>
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<td>Manila Stock Exchange</td>
<td>MSE Com’l &amp; Inustil Price</td>
<td>MC</td>
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* Data sourced from DRI.
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<thead>
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<th>Americas</th>
<th>Asia Pacific</th>
<th>Europe and Africa</th>
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<td>ARS</td>
<td>Argentine peso</td>
<td>AUD Australian dollar</td>
<td>ATS Austrian shilling</td>
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<tr>
<td>CAD</td>
<td>Canadian dollar</td>
<td>HKD Hong Kong dollar</td>
<td>BEF Belgian franc</td>
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<tr>
<td>MXN</td>
<td>Mexican peso</td>
<td>IDR Indonesian rupiah</td>
<td>CHF Swiss franc</td>
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<td>USD</td>
<td>U.S. dollar</td>
<td>JPY Japanese yen</td>
<td>DEM Deutsche mark</td>
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<tr>
<td>EMB</td>
<td>EMBI+*</td>
<td>KRW Korean won</td>
<td>DKK Danish kroner</td>
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<td></td>
<td></td>
<td>MYR Malaysian ringgit</td>
<td>ESP Spanish peseta</td>
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<td></td>
<td></td>
<td>NZD New Zealand dollar</td>
<td>FIM Finnish mark</td>
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<td></td>
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<td>PHP Philippine peso</td>
<td>FRF French franc</td>
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<td>SGD Singapore dollar</td>
<td>GBP Sterling</td>
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<td>THB Thailand baht</td>
<td>IEP Irish pound</td>
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<td></td>
<td></td>
<td>TWD Taiwan dollar</td>
<td>ITL Italian lira</td>
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</table>

* EMBI+ stands for the J.P. Morgan Emerging Markets Bond Index Plus.
<table>
<thead>
<tr>
<th>Market</th>
<th>Source</th>
<th>Third Party</th>
<th>Time</th>
<th>Term Structure</th>
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<td>J.P. Morgan</td>
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<td>U.S. EST</td>
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<td>Canada</td>
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</table>

* Third party source data from Reuters Generic except for Hong Kong (Reuters HIBO), Singapore (Reuters MASX), and New Zealand (National Bank of New Zealand).

† Money market rates for Indonesia, Malaysia, and Thailand are calculated using foreign exchange forward points.

‡ Mexican rates represent secondary trading in Mexico.
<table>
<thead>
<tr>
<th>Market</th>
<th>Source</th>
<th>Time</th>
<th>Term structure</th>
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<td>J.P. Morgan</td>
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<tr>
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<tr>
<td>Japan</td>
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<td>Emerging Mkt.†</td>
<td>•</td>
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* Third party data sourced from Den Danske Bank (Denmark), NCB Stockbrokers (Ireland), National Bank of New Zealand (New Zealand), and SE Banken (Sweden).

† J. P. Morgan Emerging Markets Bond Index Plus (EMBI+).
Table 9.4
Swap zero rates: sources and term structures

<table>
<thead>
<tr>
<th>Market</th>
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<td>J.P. Morgan</td>
<td>US EST</td>
<td>2y 3y 4y 5y 7y 10y</td>
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<td>Australia</td>
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<tr>
<td>Hong Kong</td>
<td>4:30 a.m.</td>
<td></td>
<td>*   *   *   *   *   *   *</td>
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<tr>
<td>Indonesia</td>
<td>4:00 a.m.</td>
<td></td>
<td>*   *   *   *   *   *   *</td>
</tr>
<tr>
<td>Japan</td>
<td>1:00 a.m.</td>
<td></td>
<td>*   *   *   *   *   *   *</td>
</tr>
<tr>
<td>Malaysia</td>
<td>4:00 a.m.</td>
<td></td>
<td>*   *   *   *   *   *   *</td>
</tr>
<tr>
<td>New Zealand</td>
<td>3:00 p.m.</td>
<td></td>
<td>*   *   *   *   *   *   *</td>
</tr>
<tr>
<td>Thailand</td>
<td>4:00 a.m.</td>
<td></td>
<td>*   *   *   *   *   *   *</td>
</tr>
<tr>
<td>Belgium</td>
<td>10:00 a.m.</td>
<td></td>
<td>*   *   *   *   *   *   *</td>
</tr>
<tr>
<td>Denmark</td>
<td>10:00 a.m.</td>
<td></td>
<td>*   *   *   *   *   *   *</td>
</tr>
<tr>
<td>Finland</td>
<td>10:00 a.m.</td>
<td></td>
<td>*   *   *   *   *   *   *</td>
</tr>
<tr>
<td>France</td>
<td>10:00 a.m.</td>
<td></td>
<td>*   *   *   *   *   *   *</td>
</tr>
<tr>
<td>Germany</td>
<td>10:00 p.m.</td>
<td></td>
<td>*   *   *   *   *   *   *</td>
</tr>
<tr>
<td>Ireland</td>
<td>11:00 a.m.</td>
<td></td>
<td>*   *   *   *   *   *   *</td>
</tr>
<tr>
<td>Italy</td>
<td>10:00 a.m.</td>
<td></td>
<td>*   *   *   *   *   *   *</td>
</tr>
<tr>
<td>Netherlands</td>
<td>10:00 a.m.</td>
<td></td>
<td>*   *   *   *   *   *   *</td>
</tr>
<tr>
<td>Spain</td>
<td>10:00 a.m.</td>
<td></td>
<td>*   *   *   *   *   *   *</td>
</tr>
<tr>
<td>Sweden</td>
<td>10:00 a.m.</td>
<td></td>
<td>*   *   *   *   *   *   *</td>
</tr>
<tr>
<td>Switzerland</td>
<td>10:00 a.m.</td>
<td></td>
<td>*   *   *   *   *   *   *</td>
</tr>
<tr>
<td>U.K.</td>
<td>10:00 a.m.</td>
<td></td>
<td>*   *   *   *   *   *   *</td>
</tr>
<tr>
<td>ECU</td>
<td>10:00 a.m.</td>
<td></td>
<td>*   *   *   *   *   *   *</td>
</tr>
<tr>
<td>Canada</td>
<td>3:30 p.m.</td>
<td></td>
<td>*   *   *   *   *   *   *</td>
</tr>
<tr>
<td>U.S.</td>
<td>3:30 a.m.</td>
<td></td>
<td>*   *   *   *   *   *   *</td>
</tr>
</tbody>
</table>

* Third party source data from Reuters Generic except for Ireland (NCBI), Hong Kong (TFHK), and Indonesia, Malaysia, Thailand (EXOT).
### Table 9.6
Commodities: sources and term structures

<table>
<thead>
<tr>
<th>Commodity</th>
<th>Source</th>
<th>Time, U.S. EST</th>
<th>Term structure</th>
</tr>
</thead>
<tbody>
<tr>
<td>WTI Light Sweet Crude</td>
<td>NYMEX*</td>
<td>3:10 p.m.</td>
<td>•</td>
</tr>
<tr>
<td>Heating Oil</td>
<td>NYMEX</td>
<td>3:10 p.m.</td>
<td>•</td>
</tr>
<tr>
<td>NY Harbor #2 unleaded gas</td>
<td>NYMEX</td>
<td>3:10 p.m.</td>
<td>•</td>
</tr>
<tr>
<td>Natural gas</td>
<td>NYMEX</td>
<td>3:10 p.m.</td>
<td>•</td>
</tr>
<tr>
<td>Aluminum</td>
<td>LME†</td>
<td>11:20 a.m.</td>
<td>•</td>
</tr>
<tr>
<td>Copper</td>
<td>LME</td>
<td>11:15 a.m.</td>
<td>•</td>
</tr>
<tr>
<td>Nickel</td>
<td>LME</td>
<td>11:10 a.m.</td>
<td>•</td>
</tr>
<tr>
<td>Zinc</td>
<td>LME</td>
<td>11:30 a.m.</td>
<td>•</td>
</tr>
<tr>
<td>Gold</td>
<td>LME</td>
<td>11:00 a.m.</td>
<td>•</td>
</tr>
<tr>
<td>Silver</td>
<td>LFOE‡</td>
<td>11:00 a.m.</td>
<td>•</td>
</tr>
<tr>
<td>Platinum</td>
<td>LPPA§</td>
<td>11:00 a.m.</td>
<td>•</td>
</tr>
</tbody>
</table>

* NYMEX (New York Mercantile Exchange)
† LME (London Metals Exchange)
‡ LFOE (London futures and Options Metal Exchange)
§ LPPA (London Platinum & Palladium Association)
Estimating volatility using financial time series

- SMA: simple moving average model (traditional approach).
- EWMA: exponentially weighted moving average model (RiskMetrics).
- ARCH and GARCH models (Nobel Prize).
Daily Returns of the S&P 500 Index

<table>
<thead>
<tr>
<th>Period</th>
<th>Mean</th>
<th>Std</th>
</tr>
</thead>
<tbody>
<tr>
<td>1962–2015</td>
<td>0.03%</td>
<td>1.01%</td>
</tr>
<tr>
<td>1962–2006</td>
<td>0.03%</td>
<td>0.93%</td>
</tr>
</tbody>
</table>
The Simple Moving Average Model

- Unlike expected returns, volatility can be measured with better precision using higher frequency data. So let’s use daily data.
- Some have gone into higher frequency by using intra-day data. But micro-structure noises such as bid/ask bounce start to dominate in the intra-day domain. So let’s not go there in this class.
- Suppose in month $t$, there are $N$ trading days, with $R_n$ denoting $n$-th day return. The simple moving average (SMA) model:

$$\sigma = \sqrt{\frac{1}{N} \sum_{n=1}^{N} (R_n)^2}$$

- To get an annualized number: $\sigma \times \sqrt{252}$. (252 trading days per year).
Whether or not to take out $\mu$?

- The industry convention is such that $(R_t - \mu)^2$ is replaced by $R_t^2$ in the volatility calculation.

- The reason is that, at daily frequency, $\mu^2$ is too small compared with $E(R^2)$. Recall, $\mu$ is several basis points while $\sigma$ is close to 1%.

- So instead of going through the trouble of doing $E(R^2) - \mu^2$, people just do $E(R^2)$. 
Volatility estimates using the simple moving average (SMA) model
How precise are SMA volatility estimates?

SMA estimates of $\sigma$ and their 95% confidence intervals

- 95% Confidence, Upper
- 95% Confidence, Lower

Annualized Volatility (%)

- 140
- 120
- 100
- 80
- 60
- 40
- 20
- 0

Year:
- 1970
- 1980
- 1990
- 2000
- 2010
What about SMA mean estimates?

SMA estimates of $\mu$ and their 95% confidence intervals

- Monthly Average of Daily Returns (%)
- 95% Confidence, Upper
- 95% Confidence, Lower
Why does volatility change over time?

- If the rate of information arrival is time-varying, so is the rate of price adjustment, causing volatility to change over time.

- The time-varying volatility of the market return is related to the time-varying volatility of a variety of economic variables, including inflation, unemployment rate, money growth and industrial production.

- Stock market volatility increases with financial leverage: a decrease in stock price causes an increase in financial leverage, causing volatility to increase.

- Investors’ sudden changes of risk attitudes, changes in market liquidity, and temporary imbalance of supply and demand could all cause market volatility to change over time.
Time-varying volatility and business cycles

(The shaded areas are the NBER dated peak to trough)
SMA vs. Option-Implied

Annualized Volatility (%)

SMA Vol Estimator
CBOE VXO

2000
2010
1990
0
20
40
60
80
100
120
140
160
VXO vs. VIX

Annualized Volatility (%)

Exponentially weighted moving average model

- The simple moving average (SMA) model fixes a time window and applies equal weight to all observations within the window.
- In the exponentially weighted moving average (EWMA) model, the more recent observation carries a higher weight in the volatility estimate.
- The relative weight is controlled by a decay factor $\lambda$.
- Suppose $R_t$ is today’s realized return, $R_{t-1}$ is yesterday’s, and $R_{t-n}$ is the daily return realized $n$ days ago. Volatility estimate $\sigma$:

\[
\text{Equally Weighted:} \quad \sqrt{\frac{1}{N} \sum_{n=0}^{N-1} (R_{t-n})^2} \\
\text{Exponentially Weighted:} \quad \sqrt{(1 - \lambda) \sum_{n=0}^{N-1} \lambda^n (R_{t-n})^2}
\]
weight on past observations

\[
\lambda = 0.8 \\
\lambda = 0.94 \\
\lambda = 0.97
\]

days in the past

Fall 2017
Jun Pan, MIT Sloan
Calculating equally and exponentially weighted volatility

<table>
<thead>
<tr>
<th>Date</th>
<th>Return USD/DEM (%)</th>
<th>Return squared (%)</th>
<th>Equal weight (I = 20)</th>
<th>Exponential weight (λ = 0.94)</th>
<th>Equally weighted, B × C</th>
<th>Exponentially weighted, B × D</th>
</tr>
</thead>
<tbody>
<tr>
<td>28-Mar-96</td>
<td>0.634</td>
<td>0.402</td>
<td>0.05</td>
<td>0.019</td>
<td>0.020</td>
<td>0.007</td>
</tr>
<tr>
<td>29-Mar-96</td>
<td>0.115</td>
<td>0.013</td>
<td>0.05</td>
<td>0.020</td>
<td>0.001</td>
<td>0.000</td>
</tr>
<tr>
<td>1-Apr-96</td>
<td>-0.460</td>
<td>0.211</td>
<td>0.05</td>
<td>0.021</td>
<td>0.011</td>
<td>0.004</td>
</tr>
<tr>
<td>2-Apr-96</td>
<td>0.094</td>
<td>0.009</td>
<td>0.05</td>
<td>0.022</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>3-Apr-96</td>
<td>0.176</td>
<td>0.031</td>
<td>0.05</td>
<td>0.024</td>
<td>0.002</td>
<td>0.001</td>
</tr>
<tr>
<td>4-Apr-96</td>
<td>-0.088</td>
<td>0.008</td>
<td>0.05</td>
<td>0.025</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>5-Apr-96</td>
<td>-0.142</td>
<td>0.020</td>
<td>0.05</td>
<td>0.027</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td>8-Apr-96</td>
<td>0.324</td>
<td>0.105</td>
<td>0.05</td>
<td>0.029</td>
<td>0.005</td>
<td>0.003</td>
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<tr>
<td>9-Apr-96</td>
<td>-0.943</td>
<td>0.889</td>
<td>0.05</td>
<td>0.030</td>
<td>0.044</td>
<td>0.027</td>
</tr>
<tr>
<td>10-Apr-96</td>
<td>-0.528</td>
<td>0.279</td>
<td>0.05</td>
<td>0.032</td>
<td>0.014</td>
<td>0.009</td>
</tr>
<tr>
<td>11-Apr-96</td>
<td>-0.107</td>
<td>0.011</td>
<td>0.05</td>
<td>0.034</td>
<td>0.001</td>
<td>0.000</td>
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<tr>
<td>12-Apr-96</td>
<td>-0.160</td>
<td>0.026</td>
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<tr>
<td>15-Apr-96</td>
<td>-0.445</td>
<td>0.198</td>
<td>0.05</td>
<td>0.039</td>
<td>0.010</td>
<td>0.008</td>
</tr>
<tr>
<td>16-Apr-96</td>
<td>0.053</td>
<td>0.003</td>
<td>0.05</td>
<td>0.041</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>17-Apr-96</td>
<td>0.152</td>
<td>0.023</td>
<td>0.05</td>
<td>0.044</td>
<td>0.001</td>
<td>0.001</td>
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<tr>
<td>18-Apr-96</td>
<td>-0.318</td>
<td>0.101</td>
<td>0.05</td>
<td>0.047</td>
<td>0.005</td>
<td>0.005</td>
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<tr>
<td>19-Apr-96</td>
<td>0.424</td>
<td>0.180</td>
<td>0.05</td>
<td>0.050</td>
<td>0.009</td>
<td>0.009</td>
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<tr>
<td>22-Apr-96</td>
<td>-0.708</td>
<td>0.501</td>
<td>0.05</td>
<td>0.053</td>
<td>0.025</td>
<td>0.027</td>
</tr>
<tr>
<td>23-Apr-96</td>
<td>-0.105</td>
<td>0.011</td>
<td>0.05</td>
<td>0.056</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td>24-Apr-96</td>
<td>-0.257</td>
<td>0.066</td>
<td>0.05</td>
<td>0.060</td>
<td>0.003</td>
<td>0.004</td>
</tr>
</tbody>
</table>

Standard deviation: Equally weighted 0.393, Exponentially weighted 0.333

Source: RiskMetrics—Technical Document

Fall 2017
Jun Pan, MIT Sloan
SMA and EWMA Estimates after a Crash

*Chart 5.2*
Log price changes in GBP/DEM and VaR estimates (1.65σ)

Computing EWMA recursively

• One attractive feature of the exponentially weighted estimator is that it can be computed recursively.

• You will appreciate this convenience if you have to compute the EWMA volatility estimator in Excel.

• Let $\sigma_t$ be the EWMA volatility estimator using all the information available on day $t - 1$ for the purpose of forecasting the volatility on day $t$.

• Moving one day forward, it’s now day $t$. After the day is over, we observe the realized return $R_t$.

• We now need to update our EWMA volatility estimator $\sigma_{t+1}$ using the newly arrived information (i.e. $R_t$). It turns out that we can do so by

$$\sigma_{t+1}^2 = \lambda \sigma_t^2 + (1 - \lambda) R_t^2$$
What about the first observation?

• The recursive formula has to start from the beginning:

\[ \sigma_2^2 = \lambda \sigma_1^2 + (1 - \lambda) R_1^2 \]

So what to use for \( \sigma_1 \)?

• In practice, the choice of \( \sigma_1 \) does not matter in any significant way after running the iterative process long enough:

\[ \sigma_3^2 = \lambda \sigma_2^2 + (1 - \lambda) R_2^2 \]

\[ = \lambda^2 \sigma_1^2 + (1 - \lambda) (\lambda R_1^2 + R_2^2) \]

\[ \sigma_4^2 = \lambda \sigma_3^2 + (1 - \lambda) R_3^2 \]

\[ = \lambda^3 \sigma_1^2 + (1 - \lambda) (\lambda^2 R_1^2 + \lambda R_2^2 + R_3^2) \]

\[ \vdots \]

\[ \sigma_t^2 = \lambda^{t-1} \sigma_1^2 + (1 - \lambda) \left( \lambda^{t-2} R_1^2 + \ldots + R_{t-1}^2 \right) \]
• A good idea is to have the iterative process run for a while (say a few months) before recording volatility estimates.

• (Prof. Pan’s Choice:) I like to set \( \sigma_1 = \text{std}(R) \), which is the “unconditional” or sample standard deviation of \( R \). The logic is that if I don’t have any information about \( \sigma_1 \) at the beginning of the volatility estimation, I might as well use the unconditional estimate of \( \sigma \).

• (The industry practice:) It is typical to set \( \sigma^2_2 = R^2_1 \) and start the recursive process from \( \sigma_3 \). The rationale is that \( \sigma_1 \) is unknowable and the only data we have at time 1 is \( R_1 \). So \( R^2_1 \) is our best estimate for \( \sigma^2_2 \). This approach is adopted by most of the practitioners, including RiskMetrics.
Dating Convention for $\sigma_t$

- The dating convention adopted by most people:

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

The rationale is that this $\sigma$ is estimated for the purpose of forecasting the next period’s volatility. So it should be dated as $\sigma_{t+1}$.

- (Prof. Pan’s Choice:) I actually like to use

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

The rationale is that at time $t$, I am forming an estimate $\sigma_t$ using all of the information available to me at time $t$.

- I will always use the main-stream approach and date it by $\sigma_{t+1}$. 
Decay factor, Strong or Weak?

- A strong decay factor (that is, small $\lambda$) underweights the far away events more strongly, making the effective sample size smaller.

- A strong decay factor improves on the timeliness of the volatility estimate, but that estimate could be noisy and suffers in precision.

- On the other hand, a weak decay factor improves on the smoothness and precision, but that estimate could be sluggish and slow in response to changing market conditions.

- So there is a tradeoff.
Annualized EWMA Volatility Estimate using Daily S&P 500 Index Returns

Red line: $\lambda = 0.8$

Blue line: $\lambda = 0.94$
Annualized EWMA Volatility Estimate using Daily S&P 500 Index Returns

\[ \lambda = 0.97 \]

\[ \lambda = 0.94 \]
Picking the optimal decay factor based on volatility forecast

- RiskMetrics sets $\lambda = 0.94$ in estimating volatility and correlation. One of their key criteria is to minimize the forecast error.

- We form $\sigma_{t+1}$ on day $t$ in order to forecast the next-day volatility. So after observing $R_{t+1}$, we can check how good $\sigma_{t+1}$ is in doing its job.

- This leads to the daily root mean squared prediction error

$$RMSE = \sqrt{\frac{1}{T} \sum_{t=1}^{T} (R_{t+1}^2 - \sigma_{t+1}^2)^2}$$

- The deciding factor of RMSE is our choice of $\lambda$. For my running example (daily S&P 500 index returns 2007-2010):

<table>
<thead>
<tr>
<th>$\lambda$</th>
<th>0.80</th>
<th>0.9075*</th>
<th>0.94</th>
<th>0.97</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
<td>8.1844</td>
<td>8.0124</td>
<td>8.0544</td>
<td>8.2444</td>
</tr>
</tbody>
</table>
Maximum Likelihood Estimation

- The gold standard in any estimation is maximum likelihood estimation, because it is the most efficient method. So let’s see what MLE has to say about the optimal $\lambda$.

- We assume that conditioning on the volatility estimate $\sigma_{t+1}$, the stock return $R_{t+1}$ is normally distributed:

$$f (R_{t+1} | \sigma_{t+1}) = \frac{1}{\sqrt{2\pi} \sigma_{t+1}} e^{-\frac{R_{t+1}^2}{2\sigma_{t+1}^2}}$$

- Take natural log of $f$:

$$\ln f (R_{t+1} | \sigma_{t+1}) = -\ln \sigma_{t+1} - \frac{R_{t+1}^2}{2\sigma_{t+1}^2}$$

I dropped $2\pi$ since it will not affect anything we will do later.
• We now add them up to get what econometricians call log-likelihood (llk):

$$
llk = -\sum_{t=1}^{T} \left( \ln \sigma_{t+1} + \frac{R_{t+1}^2}{2\sigma_{t+1}^2} \right)
$$

• The only deciding factor in llk is our choice of $\lambda$. It turns out that the best $\lambda$ is the one that maximizes llk.

• In practice, we take -llk and minimize -llk instead of maximizing llk.

• For my running example (daily S&P 500 index return 2007-2010), I find the optimal $\lambda$ that minimizes -llk is 0.9320. Not exactly the same as the optimal $\lambda$ of 0.9075 that minimizes RMSE, but these two are reasonably close.
The Surface of Planet MLE

\[\text{Plot of } -\ln k \text{ vs. } \lambda\]
The ARCH and GARCH models

- The ARCH model, autoregressive conditional heteroskedasticity, was proposed by Professor Robert Engle in 1982. The GARCH model is a generalized version of ARCH.

- ARCH and GARCH are statistical models that capture the time-varying volatility:

\[ \sigma_{t+1}^2 = a_0 + a_1 R_t^2 + a_2 \sigma_t^2 \]

- As you can see, it is very similar to the EWMA model. In fact, if we set \( a_0 = 0, a_2 = \lambda, \) and \( a_1 = 1 - \lambda, \) we are doing the EWMA model.

- So what’s the value added? This model has three parameters while the EWMA has only one. So it offers more flexibility (e.g., allows for mean reversion and better captures volatility clustering).

- But I think EWMA is good enough for us, for now.

8 October 2003

The Royal Swedish Academy of Sciences has decided that the Bank of Sweden Prize in Economic Sciences in Memory of Alfred Nobel, 2003, is to be shared between

Robert F. Engle
New York University, USA

“for methods of analyzing economic time series with time-varying volatility (ARCH)”

and

Clive W. J. Granger
University of California at San Diego, USA

“for methods of analyzing economic time series with common trends (cointegration)”.
EWMA covariances and correlations

- Our goal is to create the variance-covariance matrix for the key risk factors influencing our portfolio.

- For the moment, let’s suppose that there are only two risk factors affecting our portfolio.

- Let $R^A_t$ and $R^B_t$ be the day-$t$ realized returns of these two risk factors. The covariance between A and B:

$$\text{cov}_{t+1} = \lambda \text{cov}_t + (1 - \lambda) R^A_t \times R^B_t$$

- And their correlation:

$$\text{corr}_{t+1} = \frac{\text{cov}_{t+1}}{\sigma^A_{t+1} \sigma^B_{t+1}}$$

where $\sigma^A_{t+1}$ and $\sigma^B_{t+1}$ are the EWMA volatility estimates.
The negative correlation between $R^M_t$ and $\Delta VIX$

- Monthly returns $R^M_t$ on the stock market portfolio is highly negatively correlated with monthly changes in VIX: -69.41%.
- Now let’s apply our EWMA approach, which will give us a time-series of correlations between these two risk factors.
- We see an interesting time-series pattern of the negative correlation between daily stock returns and daily changes in VIX.
- In particular, this correlation has become more negative in recent years.
- (CBOE started to offer futures trading on VIX on March 26, 2004.)
- corr($R^M, \Delta VIX$)

\[
\lambda = 0.9533 \text{(MLE Optimal)}
\]

\[
\lambda = 0.98
\]
The CBOE Volatility Index (pre-1990: VXO; post-1990: VIX)
Calculating Volatility for a Portfolio

- Suppose that our portfolio has two important risk factors, whose daily returns are $R^A$ and $R^B$, respectively.
- Performing risk mapping using individual positions, the portfolio weights on these two risk factors are $w_A$ and $w_B$.
- Let’s focus only on the risky part of our portfolio and leave out the cash part. So let’s normalize the weights so that $w_A^2 + w_B^2 = 1$. Let’s assume our risk portfolio has a market value of $100$ million today.
- We apply EWMA to get time-series of their volatility estimates $\sigma^A_t$ and $\sigma^B_t$, and correlation estimates $\rho_{tAB}$. And our portfolio volatility is
  \[ \sigma^2_t = w_A^2 \times (\sigma^A_t)^2 + w_B^2 \times (\sigma^B_t)^2 + 2 \times w_A \times w_B \times \rho_{tAB} \times \sigma^A_t \times \sigma^B_t \]
- It is in fact easier to do this calculation using matrix operations, especially when you have to deal with hundreds of risk factors.
Variance-Covariance Matrix

- We construct a variance-covariance matrix for risk factors A and B:

\[ \Sigma_t = \begin{pmatrix} \sigma_t^A & \rho_t^{AB} \sigma_t^A \sigma_t^B \\ \rho_t^{AB} \sigma_t^A \sigma_t^B & \sigma_t^B \end{pmatrix} \]

- It is a $2 \times 2$ matrix, since we have only two risk factors. If you have 100 risk factors in your portfolio, then you will have a $100 \times 100$ matrix. For example, in JPMorgan’s RiskMetrics, 480 risk factors were used. In Goldman’s annual report, 70,000 risk factors were mentioned.

- A risk manager deals with this type of matrices everyday and the dimension of the matrix can easily be more than 100, given the institution’s portfolio holdings and risk exposures.

- Notice the timing: for $\sigma_t$, we use all returns up to day $t - 1$ for the purpose of forecasting volatility for day $t$. 
Portfolio Volatility

- Let’s write our weights in vector form, time stamped by today, t-1,

\[ w_{t-1} = \begin{pmatrix} w_{t-1}^A \\ w_{t-1}^B \end{pmatrix} \]

- Our portfolio volatility is

\[ \sigma_t^2 = \begin{pmatrix} w_{t-1}^A & w_{t-1}^B \end{pmatrix} \times \begin{pmatrix} (\sigma_t^A)^2 & \rho_t^{AB} \sigma_t^A \sigma_t^B \\ \rho_t^{AB} \sigma_t^A \sigma_t^B & (\sigma_t^B)^2 \end{pmatrix} \times \begin{pmatrix} w_{t-1}^A \\ w_{t-1}^B \end{pmatrix} \]

- Using the notation we’ve developed so far, we can also write

\[ \sigma_t^2 = w'_{t-1} \times \Sigma_t \times w_{t-1}, \]

which involves using mmult and transpose in Excel.
Portfolio VaR

- Let \( \sigma \) be the daily volatility estimate of the portfolio. Then the 95% one-day VaR is,

\[
\text{VaR} = \text{portfolio value} \times 1.645 \times \sigma
\]

- The 99% tail event corresponds to a -2.326 \( \sigma \) move away from the mean.

The 95% tail event corresponds to -1.645 \( \sigma \).
• Assuming the market value of our risk portfolio is $100 million, the one-day loss in portfolio value associated with the 5% worst-case scenario is

$$100M \times 1.645 \times \sigma$$

• Suppose that we have only one risk factor, which is the S&P 500 index. If today is a normal day with an average volatility around 1%, then the one-day 95% VaR is $1.645M. For the same portfolio value, if the reported VaR is much higher than $1.645M, then today must be a volatile day.

• Overall, if we fix our VaR estimate to a certain horizon, say daily, then the main drivers to the VaR estimates are: the market value and volatility of our portfolio. A reduction in VaR could be caused by a reduction in the market value (either by active risk reduction or passive loss in market value) or a reduction in market volatility.
Key Asset Classes for Market Risk Management

- What JP Morgan RiskMetrics had to offer (free of charge) back in 1996 gives a good overall picture of what kind of asset classes are involved in calculating the market risk exposure of an investment bank.

- RiskMetrics data sets: Two sets of daily estimates of future volatilities and correlations of approximately 480 rates and prices, with each data set totaling 115,000+ data points. One set is for computing short-term trading risks, the other for medium term investment risks. The data sets cover foreign exchange, government bond, swap, and equity markets in up to 31 currencies. Eleven commodities are also included.

- This set of data (equity, currency, interest rates, and commodity) is very much the domain of Market Risk Management. In addition, **Credit** and **Liquidity Risk Management** have become increasingly important. For this, good data, models, and talents on credit and liquidity are in need.
Broad Asset Classes for Market Risk Management

*from Goldman Sachs 2010 10-K form*

### Average Daily VaR

<table>
<thead>
<tr>
<th>Risk Categories</th>
<th>December 2010</th>
<th>December 2009</th>
<th>November 2008</th>
</tr>
</thead>
<tbody>
<tr>
<td>Interest rates</td>
<td>$93</td>
<td>$176</td>
<td>$142</td>
</tr>
<tr>
<td>Equity prices</td>
<td>68</td>
<td>66</td>
<td>72</td>
</tr>
<tr>
<td>Currency rates</td>
<td>32</td>
<td>36</td>
<td>30</td>
</tr>
<tr>
<td>Commodity prices</td>
<td>33</td>
<td>36</td>
<td>44</td>
</tr>
<tr>
<td>Diversification effect</td>
<td>(92)</td>
<td>(96)</td>
<td>(108)</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>$134</strong></td>
<td><strong>$218</strong></td>
<td><strong>$180</strong></td>
</tr>
</tbody>
</table>

1. Equals the difference between total VaR and the sum of the VaRs for the four risk categories. This effect arises because the four market risk categories are not perfectly correlated.