The M^6 Competition

Risk Model – Construction & Application

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Risk Modeling and Decision Making in **M**^{6}

- Role of risk left implicit in competition rules
- Competitors asked to maximize Sharpe Ratio:

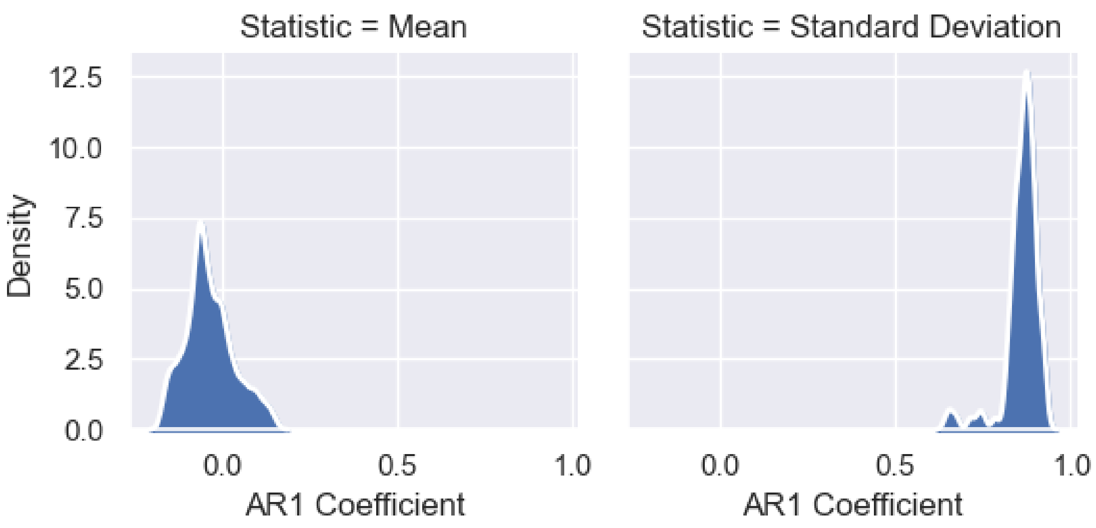
$$\mathrm{SR_w} = w\alpha / \sqrt{\mathrm{w}\Sigma\mathrm{w}'}$$

- α represents forecast return, Σ represents forecast risk
- *w* are the portfolio weights ('decisions')

Problem: Estimate Σ, Calibrate α, Choose *w*

Estimating Σ - The good news…

Distribution of AR(1) coefficient for M6 Assets:
Mean and Standard Deviation of 20 day returns



Univariate variance is **much** more persistent than return - i.e. risk is **much** easier to forecast.

Estimating Σ - The bad news…

- Σ is very large for most reasonable portfolio construction problems
  - For M6, Σ has 100 x 100 = 10,000 terms
  - We only have approximately 144 trading months of data.
  - Covariance is time varying and most of this data is too old to be very reliable
- Thus, Σ is very difficult to estimate
  - Estimation errors are guaranteed
- Errors in Σ are ruthlessly exploited by optimisation software…
  - Covariance errors mistaken for arbitrage opportunities
  - These positions get levered up in resultant portfolios

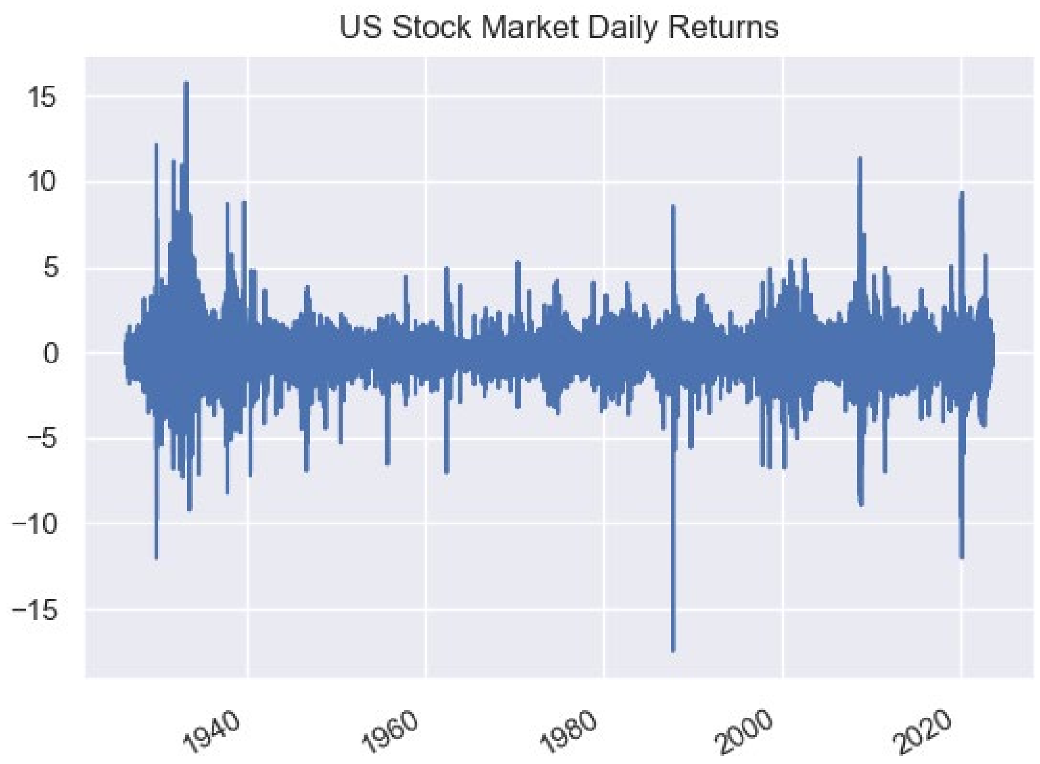
Solution: Dimension reduction and/or shrinkage

M^6 -Estimating Σ in Practice

- Take account of 'stylised facts' about volatility
- Desiderata:
  - Use readily accessible data
  - Available to participants ex-ante
  - (Relatively!) Simple tools and techniques
- Split the problem in to two components:
  1. Univariate volatility
  2. Correlation

Objective: A simple and robust risk model

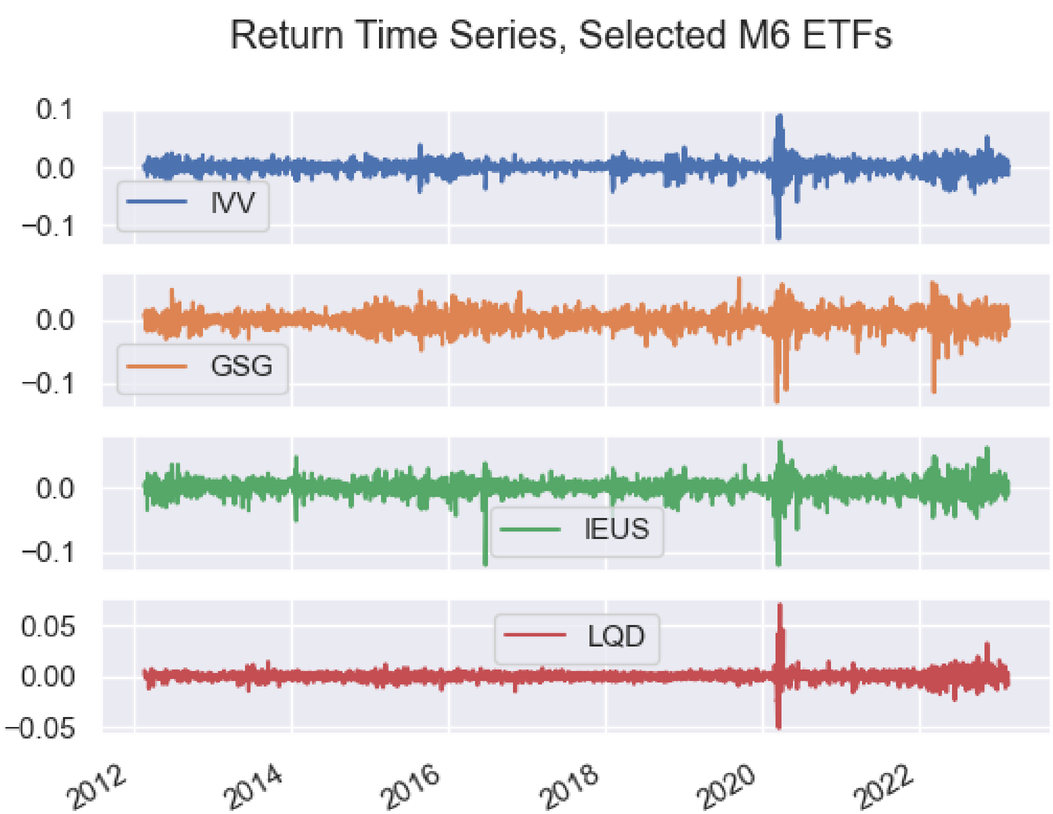
Volatility Clustering, Heteroskedasticity



Constant volatility assumption is not appropriate

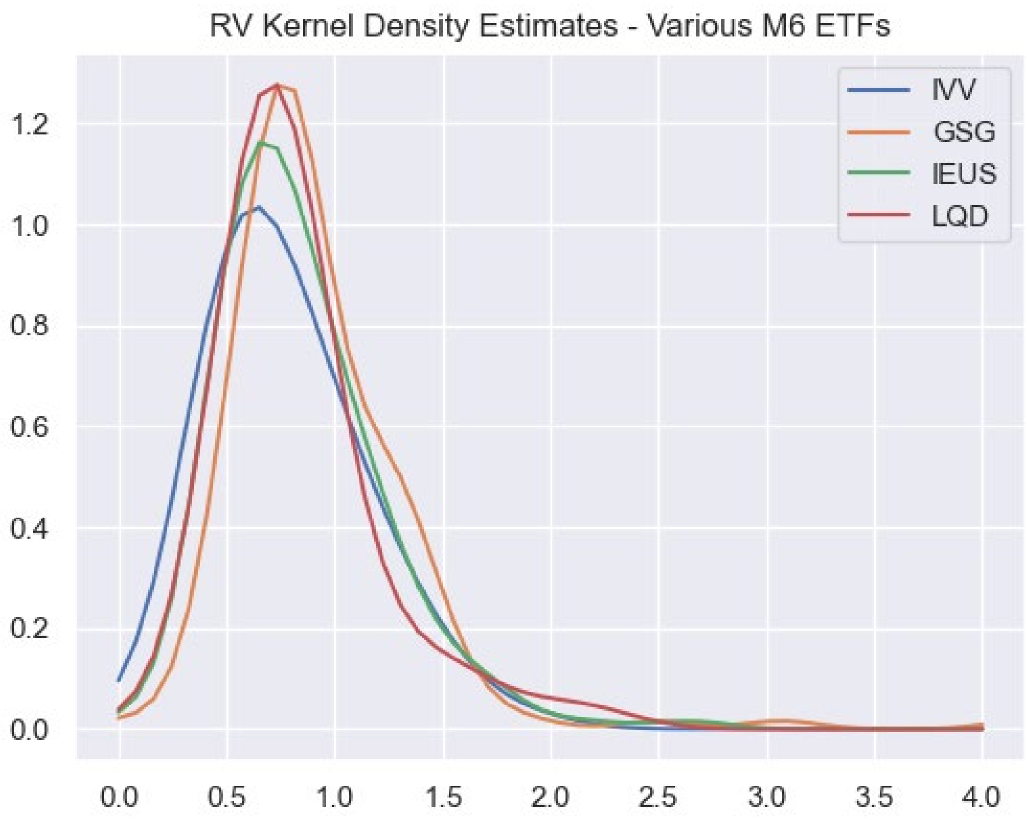
US Market Daily returns from 7/1927, source: **Kenneth R. French Data Library.**
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

Volatility spillover



Volatlity peaks & troughs often **coincide**, even for **dissimilar** assets

Exploring Centered Return Distributions



RVs - **similar** distributions for **dissimilar** assets

‘Hexp’ Volatility Model

- Model of Bollerslev et al 2018
  - Modification – uses range based daily volatility estimates
  - Models ‘centered’ volatility (less long run volatility)
- Explanatory variables
  - 4 exponentially weighted moving averages (less the long run volatility)
  - EWMA at [1,5,25,125] centers of mass
  - Plus a ‘global’ volatility factor
- Estimation
  - OLS on pooled data
  - Easy to fit
  - Global model
  - Uses all the data
  - Re-estimated Friday before each submission date

A simple, robust, proven approach

Multivariate Estimation - Technique

- Utilise a D(ynamic) C(onditional) C(orrelation) style model (Engle)
  1. Estimate univariate models
  2. Use these to standardize return series
  3. Estimate quasi – correlation of these values
- Quasi - correlation terms follow a GARCH style process:
  - i.e. for standardized asset returns x_t, y_t :

$$h_t = \omega h_0 + \alpha x_t . y_t + \beta h_{t-1}$$

- Constrain $\omega + \alpha + \beta = 1$
- Choose α, β
- h_0 is 'long run target' value

Well documented, parsimonious approach

Multivariate Estimation – The Factor Model

- Workhorse model in Finance
  - Returns expressed as a function of a small number of factors + residual
  - Significant dimension reduction
  - Lots of 'art' in choosing / specifying a model!
- For M6 we specify factors as various combinations of ETF Assets
  - Easy to do
  - No additional data required
  - Simple to explain
  - Model is 'hierarchical' – Market / Risk factors / Industries
- Estimate factor / asset covariance with DCC
  - But: Long run correlation based on a single factor model (CAPM style)
  - Provides additional shrinkage
  - Choose α, β by grid search before competition
  - Choices reflect significant shrinkage

Dimension reduction and shrinkage are **key** to sensible portfolio construction

Calibrating α

- Participants provided probabilistic forecasts
- We translate these to return forecasts using standard techniques in quantitative asset management (Grinold & Kahn / Black Litterman)
- Prior assumption:
  - Each asset has zero expected return, with SD estimated from risk model
- Forecasts are shrunk towards the prior
  - Shrinkage intensity set at 'high', 'medium' or 'low'
  - Based on realistic assumptions and historical data
  - Forecasts are thus calibrated to the risk estimates
- Alternative assumptions, in particular re consensus / equilibrium expected returns are also reasonable (eg historic equity / bond risk premia)

Realistic forecasts based on sensible risk estimates

Choosing *w* - Optimization

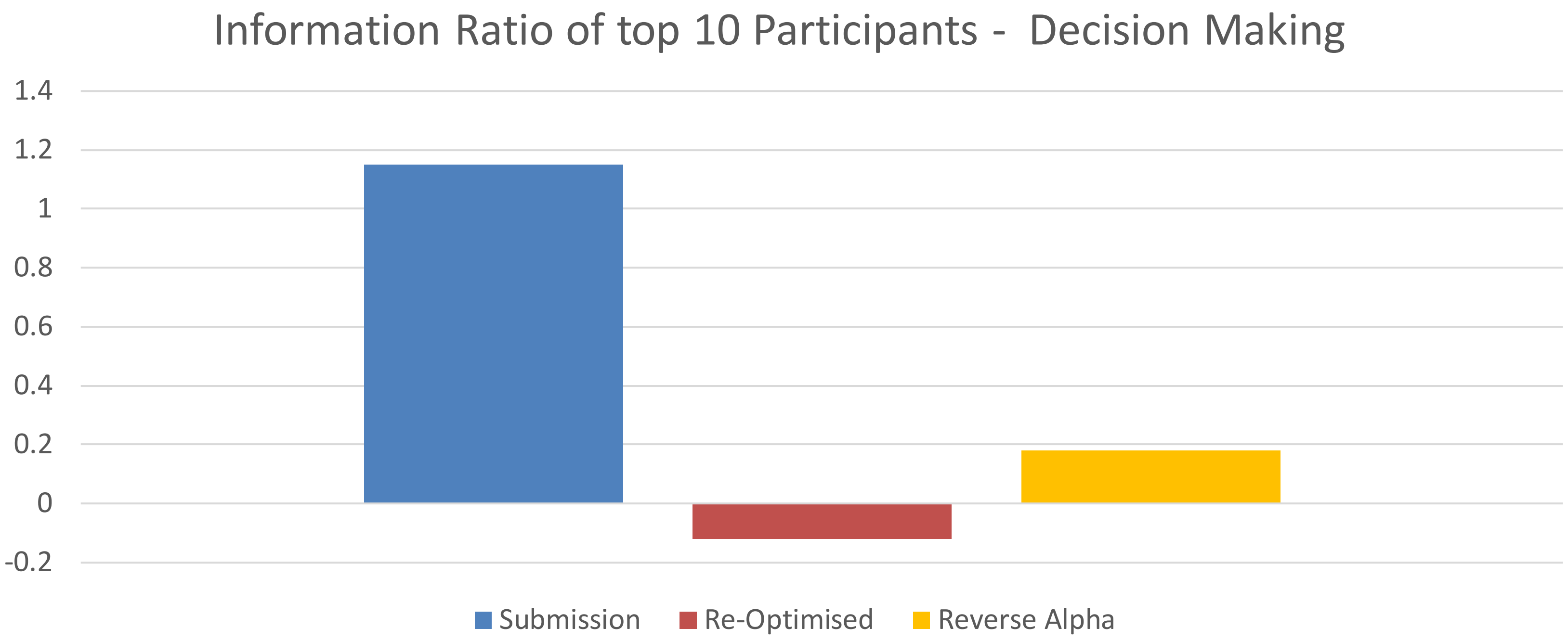
- Maximum Sharpe ratio portfolios available in closed form given certain assumptions
- These don't (quite) apply in M6
- So optimize numerically
  - Two scenarios:
    - Unconstrained
    - Risk target
- Bear in mind:
  - Diversification is famously 'the only free lunch in finance'
  - Poor implementation has a cost in terms of diversification forgone
  - Excess risk is a killer of geometric (compound) returns
- Reverse optimization
  - If w is considered known, what can we deduce about α?

Key Results – Part 1

IC Quintile	Realized IC	Submission Risk (Ex Ante) %	Optimal Risk (Ex Ante) %	Submission Return (Ex Post) %	Optimal Return (Ex Post) %	Submission IR (Ex Post)	Optimal IR (Ex Post)
1	-0.24	10.8	6.2	-12.4	-20.9	-1.4	-2.8
2	-0.08	11.7	5.9	-5.2	-7.9	-0.8	-1.2
3	0.00	11.9	5.9	2.5	-0.1	0.5	-0.1
4	0.08	11.5	5.8	4.7	8.3	0.7	1.6
5	0.22	10.3	6.1	16.5	25.4	2.5	4.3

Overconfidence – Participants systematically assumed more risk than could be justified by the accuracy of their forecasts. Within the optimized portfolios, we observe a much clearer relationship between α and IR

Key Results Part II



No evidence that superior returns come from return forecasts, or are strongly related to submitted portfolios weights (given the risk model)

The M6 Competition - Risk based Analysis

Conclusions

- Participants exhibited substantial overconfidence
- We observe substantial noise in the connection between forecasts and decisions
- No evidence that results of the returns based 'decision making' competition were determined by superior information in forecasts (or portfolio weights)

Implications

1. Investors should focus on realistically assessing the accuracy of their forecasts
2. They should build and utilize simple and robust risk models
3. Only then are accurate return forecasts economically valuable
4. Investment outcomes are often a **poor** indicator of investment insight

Thank you for your attention

Questions?

If you would like to learn more about M6 visit

https://mofc.unic.ac.cy/the-m6-competition/