Quantitative Equity Work Flow

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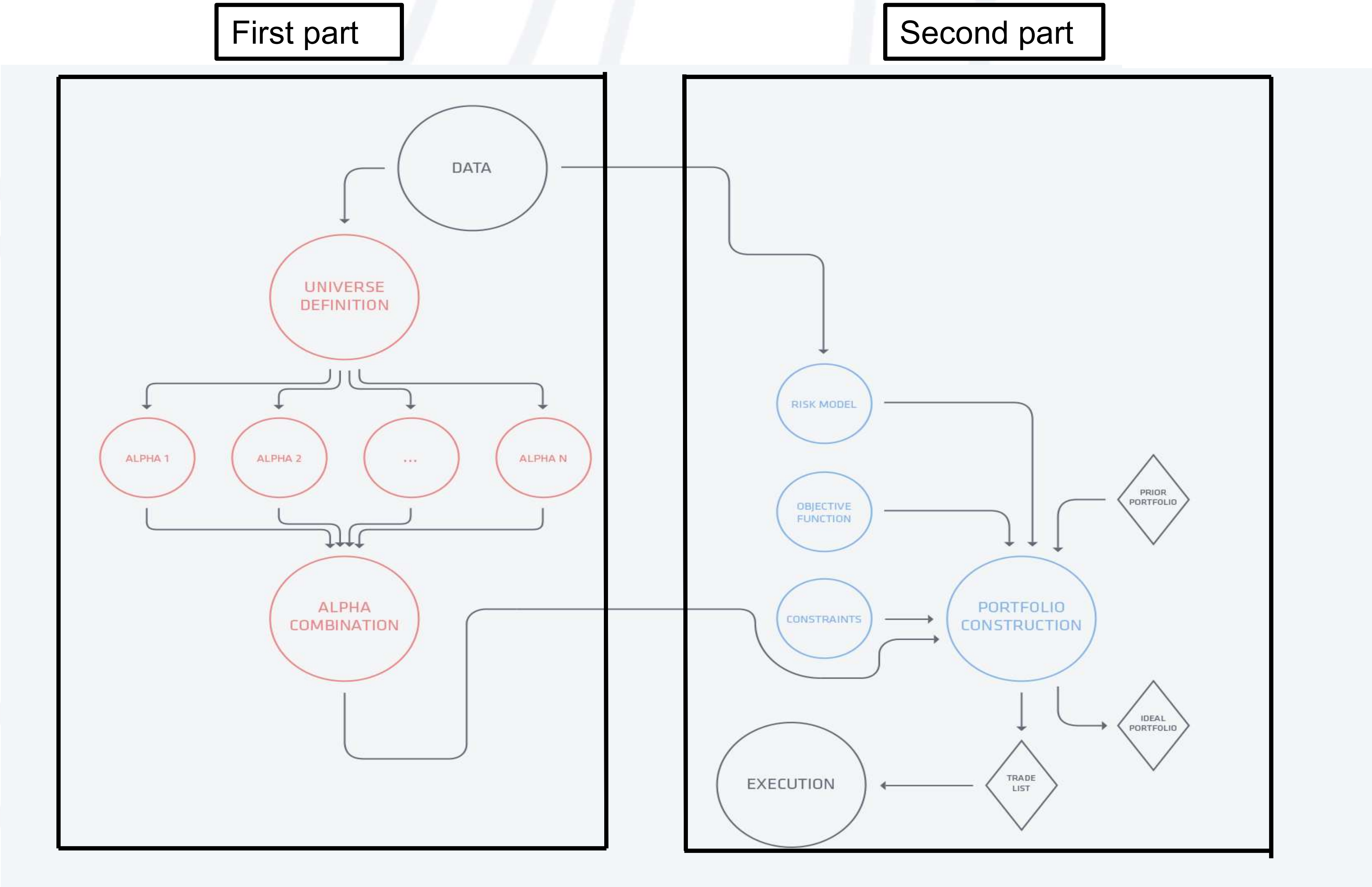
Investment Process in a Fund



Note: This process is a loop and the cycle time could be monthly, quarterly or annual.
Alpha = factor return

Six stages of Quantitative Equity Work Flow

- **First part:**

+ **Data: Mostly from FactSet, requires ongoing cleaning and fine-tuning of the database**
+ **Universe Investment: ASX 200 and MSCI AC WORLD**
+ **Factor selection: evaluating factors (attributions) to figure out which factors can better predict future stock returns?**
+ **Factor Combination: find a proper weighting to produce a return forecast which is better than the best individual factor return forecast**

- **Second part:**

+ **Portfolio Construction: maximize factors return under risk controlling and subjective constraints**
+ **Trading: minimize execution cost and impact of market**

Note: Sufficiency arises by making deliberate and thoughtful choices at each stage of the process.

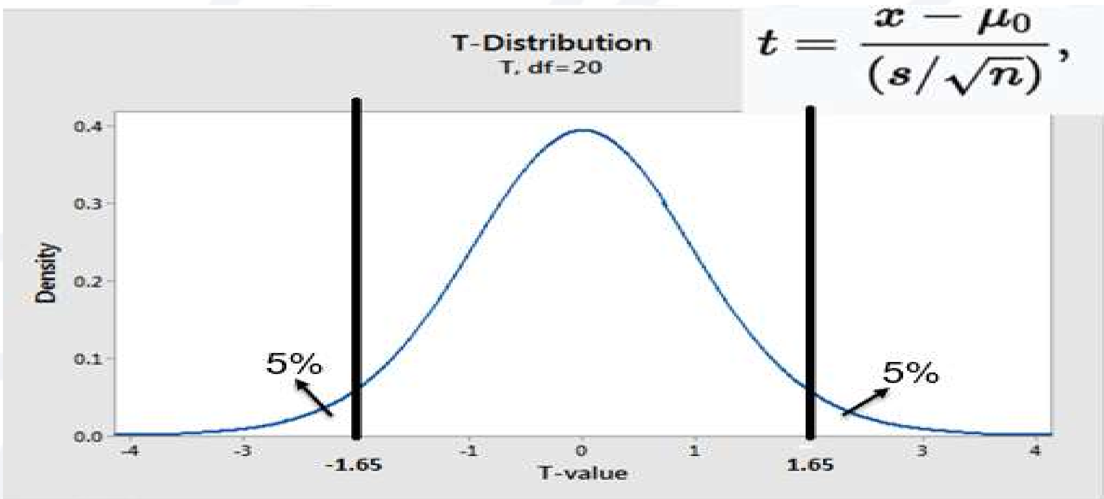
Stage 3: Factor selection

1. Rank Information Coefficient (Rank IC) test

- Rank ICs are based on the correlation of rank of forward stock returns against rank of factor Score - corr(rank(factor (t-1)), rank (return(t))) . It is calculated every month and measures the forecast power of a factor.
- Good factors should have average **rank IC > 1%.**

2. T-statistic: with Mo = 0, x = mean (Rank IC)

- **T-statistics =2** (p-value = 5%, confident level = 95%).



$$t = \frac{x - \mu_0}{(s/\sqrt{n})},$$

Stage 4: Factor combination

- **The goal at this stage is to implement a weighting scheme which takes as many good factors as possible to produce a combined factor which forecasts returns better than any individual factor.**
- **Problems:**

+ First, **how to make factors comparable with** different scales and some may have units.

By combining these raw factor scores we run the risk of applying weights that

are effectively different to the ones we intended.

+ Second, **how to optimally combine correlated factors**?

If we don't take account the correlated factor, we will cope some problems:

+ Double counting common effect of factors

+ Creating a sub-optimal in-sample model

Stage 4: Factor combination

2. Solutions:

- For combining factors, we rescale factors while preserving their order using standardization process. Typically, we choose the standardized variable to have a mean of zero and a standard deviation of one and eliminate outlier observations (winsorizing).

$$zscore_i = \frac{x_i - \bar{x}}{\sigma_x}$$

- For correlated factors, we calculated correlation matrix (ρ) for all selected factor and adjusted the IC of factors taking account to the correlation matrix. In order to that, we used the following formula of Grinold & Kahn (2000):

$$IC' = IC^T * \rho^{-1}$$

- Eliminate the factors with t-stat < 2 and IC' <1%
- For weighting factor, we weight them based on the proportion of adjusted IC over the total adjusted IC of all the factors.

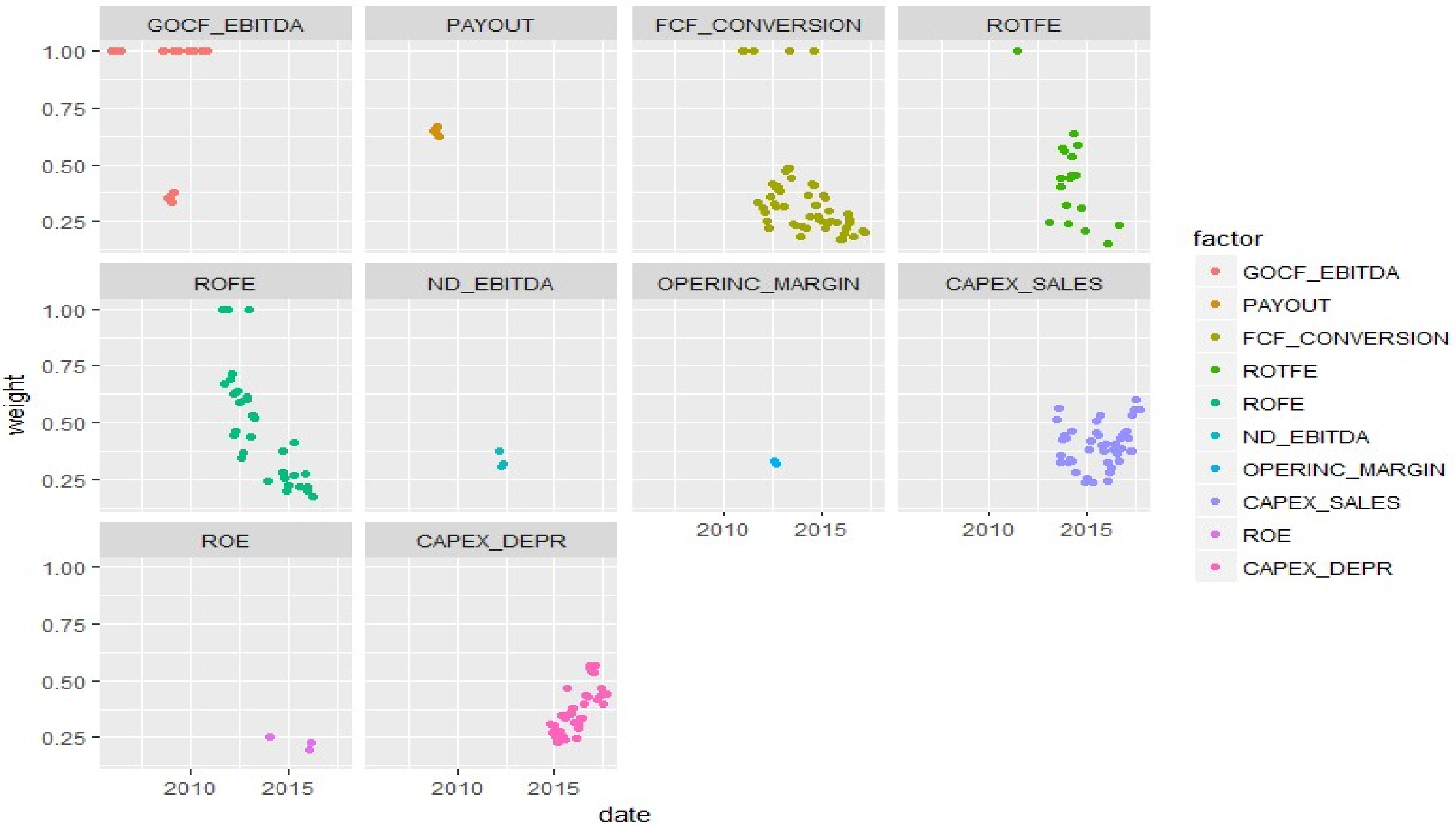
Factor rankIC correlations of MSCIWORLDG since 1996-01-31

	COST_GROWTH	AVG_BORROW_COST	ASSET_TURNOVER	FCF_CONVERSION	CAPEX_DEPR	CAPEX_SALES	ND_EQUITY	ND_OPL_EBITDAR	ND_EBITDA	FIXED_COVER_CHARGES	INTERESTCOVER	ROE	ROTFE	ROFE
ROFE	-.2	-.1	.5	.5	.3	.3	.5	.6	.7	.6	.8	.8	1	1
ROTFE	-.1	-.2	.5	.6	.4	.3	.4	.5	.6	.6	.7	.8	1	1
ROE	-.4	-.3	.2	.2	.0	.1	.4	.4	.5	.5	.6	1	.8	.8
INTERESTCOVER	.0	.4	.6	.5	.3	.4	.4	.5	.6	.9	1	.6	.7	.8
FIXED_COVER_CHARGE	.0	.2	.3	.3	.2	.2	.1	.3	.3	1	.9	.5	.6	.6
ND_EBITDA	-.1	.1	.6	.4	.3	.3	.9	1	1	.3	.6	.5	.6	.7
ND_OPL_EBITDAR	-.2	.1	.5	.3	.2	.2	.9	1	1	.3	.5	.4	.5	.6
ND_EQUITY	-.3	.1	.4	.2	.1	.1	1	.9	.9	.1	.4	.4	.4	.5
CAPEX_SALES	.4	.3	.7	.6	.8	1	.1	.2	.3	.2	.4	.1	.3	.3
CAPEX_DEPR	.6	.2	.6	.8	1	.8	.1	.2	.3	.2	.3	.0	.4	.3
FCF_CONVERSION	.5	.1	.5	1	.8	.6	.2	.3	.4	.3	.5	.2	.6	.5
ASSET_TURNOVER	.2	.4	1	.5	.6	.7	.4	.5	.6	.3	.6	.2	.5	.5
AVG_BORROW_COST	.3	1	.4	.1	.2	.3	.1	.1	.1	.2	.4	-.3	-.2	-.1
COST_GROWTH	1	.3	.2	.5	.6	.4	-.3	-.2	-.1	.0	.0	-.4	-.1	-.2

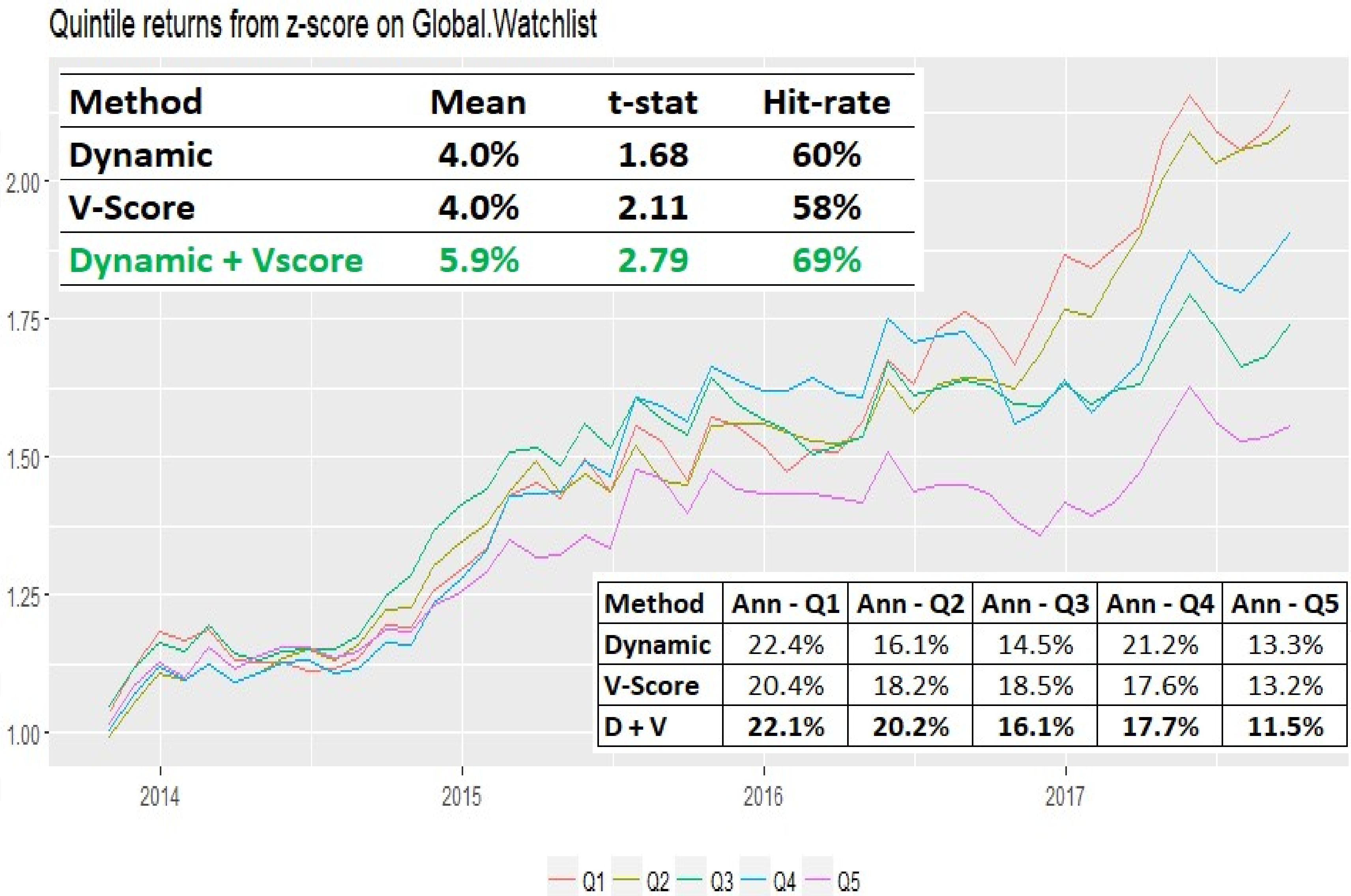
Choose the best window

	avg rankIC	rankIC t-stat	rankIC hit rate	long-short quintile return diff	number of months with *no* valid factors	number of months with only 1 or 2 factors	number of factors Aug 2017
rolling 4 years	2.4%	2.37	54%	55%	35	56	5
rolling 5 years	1.4%	1.61	52%	22%	47	65	2
rolling 6 years	1.9%	2.48	55%	93%	32	67	2
rolling 7 years	1.4%	1.99	55%	93%	33	66	2
rolling 8 years	1.1%	1.61	55%	43%	24	85	4
rolling 9 years	1.0%	1.54	55%	56%	17	97	3

Factors tend to work and working time _ MSCI AC WORRLD



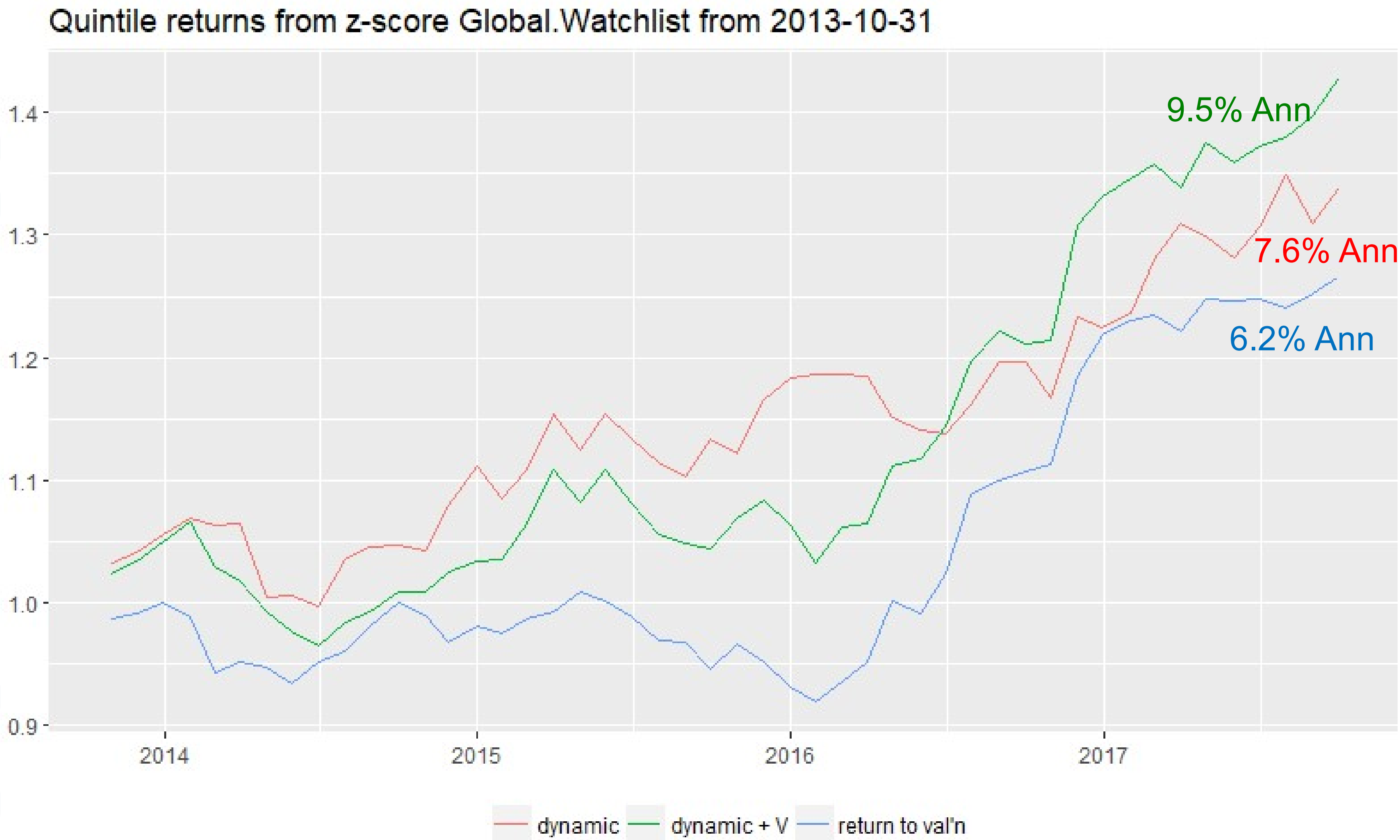
50% - 50% Combination between FinQ and CI’s V-score



Method	Mean	t-stat	Hit-rate
Dynamic	4.0%	1.68	60%
V-Score	4.0%	2.11	58%
Dynamic + Vscore	5.9%	2.79	69%

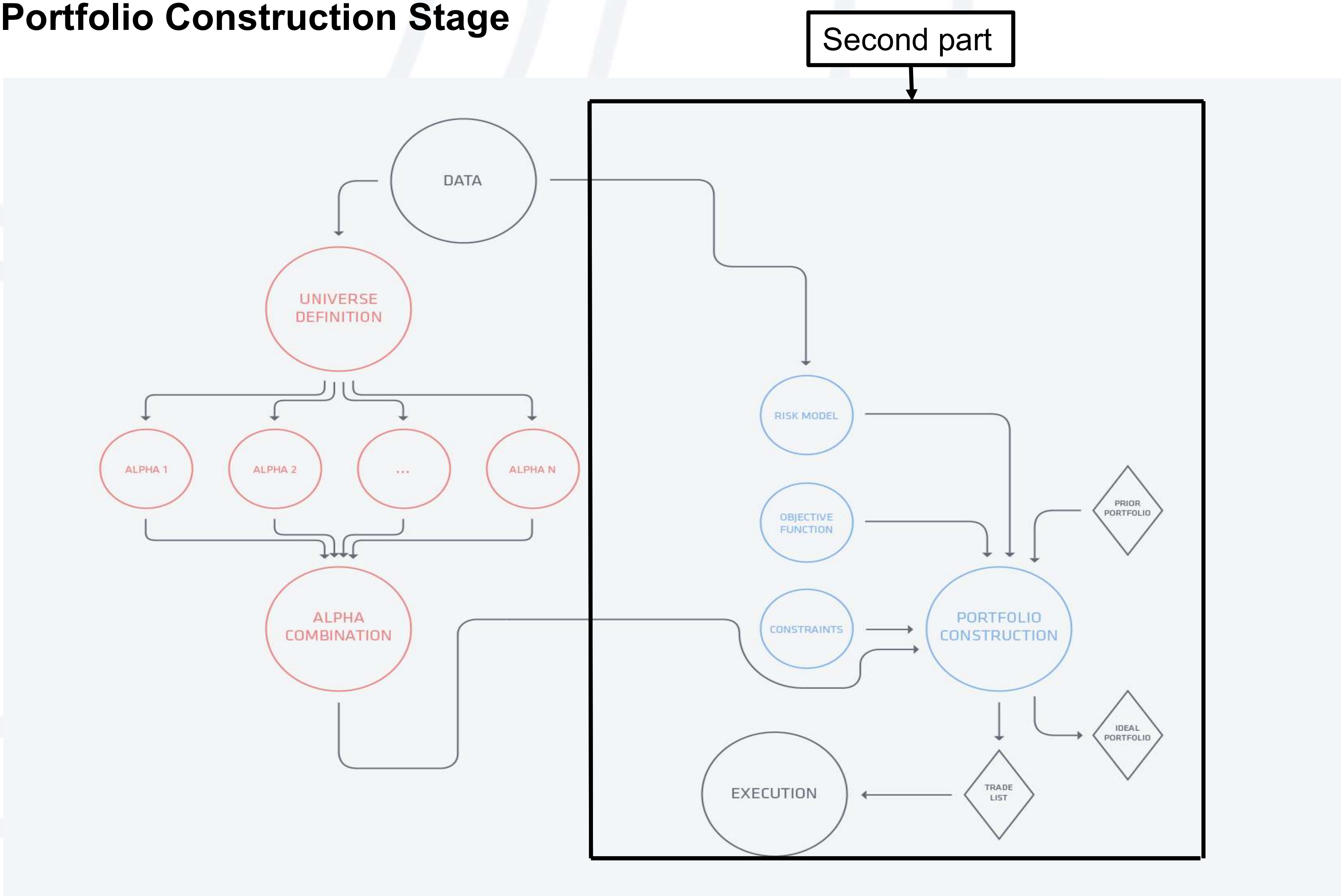
Method	Ann - Q1	Ann - Q2	Ann - Q3	Ann - Q4	Ann - Q5
Dynamic	22.4%	16.1%	14.5%	21.2%	13.3%
V-Score	20.4%	18.2%	18.5%	17.6%	13.2%
D + V	**22.1%**	**20.2%**	**16.1%**	**17.7%**	**11.5%**

Long – Short Quintile return of 3 methods



- Using Combination method between FinQ Dynamic and VOF adds 3.3% return each year on the result obtained if using only CI's VOF (6.2%).

Portfolio Construction Stage



Note: This process is a loop and the cycle time could be monthly, quarterly or annual.
Alpha = factor return

Stage 5: Portfolio Construction

- **The main object of this stage is to maximize returns under risk controlling and subjective constraints.**
- **From the portfolio and forecast return of each stock from Z-score FINQ factor model, we will try to figure out new ideal weight for portfolio.**
- **Questions need to be answered:**

  + What are the targets in the portfolio construction step?

  (maximum return, maximum Sharpe ratio, minimum risk or other objects)

  + How will the portfolio be constrained?

  (long only, max weight, turnover, …)

Performing Portfolio Optimization

Portfolio optimisation works by changing the weights of the stocks within the portfolio until the risk adjusted return of the portfolio is maximised subject to the required constraints.

$$\boldsymbol{Value\ Added = Risk\ Tolerance\ * Portfolio\ Alpha\ - Portfolio\ Risk}$$

Or mathematically

$$\boldsymbol{Value\ Added = Risk\ Tolerance\ * Weight * Forecast\ Return - Weight\ * Stock\ covariance\ variance\ matrix\ of\ risk}$$

Inputs for Optimization process:

1. An initial portfolio: Using CI's Australian Equity Fund (AEF) portfolio
2. The stock return forecast = Volatility * IC * Z-score
3. The risk model: Considered four risk factors including :
   - Size (log of market capitalisation) ;
   - Value (book to price);
   - Momentum (EPS 12Month);
   - Volatility (12 Month volatility forecast using GARCH(1,1) model)

Optimization process to find optimal weights

4. A set of fund constrains:

- Sum weight of all stock = 1
- Stocks which are listed as NZ-only can make up at most 10% of the fund
- Stocks have a maximum weight of 10%
- Industry groups have a maximum weight of 20% relative to the benchmark weight
- Small caps stocks cannot make up more than 20% fund
- Turnover <= 20% / year (*)

5. An objective:

Maximize cumulative returns based on the stock return forecast and risk models

The stock portfolio risk – Construct a structural risk model

- By properly combining risk model and return forecast model in an optimisation, our portfolio will be exposed to our return factors without unduly exposed to risk.
- Considered four risk factors: Size; Value; Momentum; Volatility
- From these four risk factors, I first find risk factor return $b_k(t)$ by regressing all the stock's risk factor exposures against the stock's forward returns. This is done every month for the entire universe over the desired period.

$$r_n(t) = \sum X_{n,k}(t).b_k(t) + u_n(t)$$

- From risk factor return, we construct risk factor covariance-variance matrix of 4 time series of risk factor returns and finally combine these together with current factor exposure to build stock covariance-variance matrix as follows:

$$V = X^T F X + \Delta$$

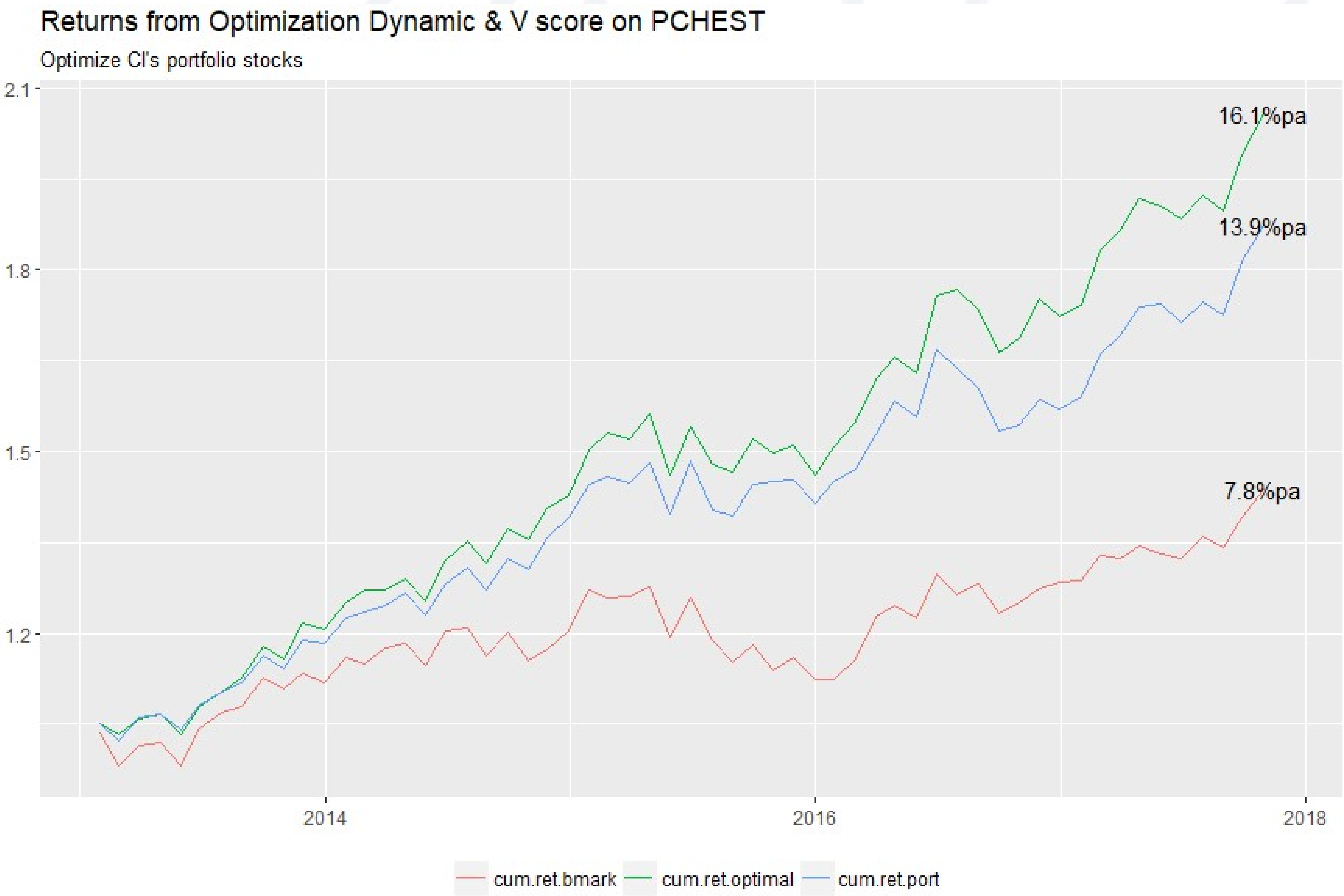
Where X = matrix of current normalised stock risk factor exposures (NxK)

F = factor covariance-variance matrix (KxK)

Δ = Var (e_t), the variance of the time series of the risk regression residuals, e_t,

where that $e_t = r_t - \sum z_i f_i$, (f_i =factor excess returns)

Optimisation Results for Maximizing Risk Adjusted return



Stage 6: Trading Stage

- **Try to obtain effective trades in the market by minimizing execution cost and impact of market**
- **Questions need to be answered:**
  - **+ How fast do we need to trade?**
  - **+ Does it make more sense to execute aggressively and immediately, considering impact of explicit cost (commission fee, tax , Bid Ask Spreads) and implicit cost (Delay cost, Price Movement Risk, Market Impact Cost, Opportunity Cost)?**

First PHD Topic: Weak-form efficiency of ASEAN markets

Research question: can stock returns be predicted from return histories

Previous studies:

- **Can not reflect change of predictability over time.**
- **Findings are inconsistent in Thailand and Singapore.**
- **Out of date data in other markets.**

My study:

- **Better methodology which allows for reflect change of predictability over time: AVR, AQ and JS tests over moving sub-sample windows.**
- **Updated data to 2015**

First PHD Topic: Weak-form efficiency of ASEAN markets

- Methodology: AVR (Kim, 2009), AQ (Escanciano & Lobato, 2009) and J and Shamsuddin, 2008) over moving sub-sample windows.
- Data from 31/08/1999 to 26/08/2015 in stock indices of 5 stock markets: Singapore, Thailand, Indonesia, Malaysia and Philippines.
- Results:
  - Thailand and Singapore markets can not be predicted for investigated period.
  - Philippines and Indonesian stock markets can not be predicted after GFC
  - Malaysian stock market can be predicted after 2013
  - There is evidence of changing predictability over time
  - Financial liberalisation has positive impact on ASEAN markets

Second PHD Topic: Stock Return Predictability of ASEAN markets

- **Are stock returns predictable from economic, financial and technical predictors?**

Previous studies:

- **Mainly on US markets (little on the ASEAN markets)**
- **Methodological issues**

  + Lag order 1 (danger of model mis-specification)

  + Using a single predictor

  + Stambaugh bias

- **Single-predictor model.**

My study:

- **Better methodology: general lag order, Correction for Stambaug bias, prevent non-stationary situation,**
- **Multi-predictor model.**

Second PHD Topic: Stock Return Predictability of ASEAN markets

- **Methodology: Predictive regression model and 6 predictors: financial ratios (DY,EP), economic indicators (TBILL, TERM), technical variables (PRES, CVM).**
- **Data from 05/1990 to 11/2015 in stock indices of 5 stock markets: Singapore, Thailand, Indonesia, Malaysia and Philippines.**
- **Results:**
  - **Stock returns are predictable in-sample**
  - **But the effect sizes of predictability are found not to be economically strong**
  - **The out-of-sample return predictability is poor**
  - **In terms of utility gains, investors will not achieve any significant economic profits.**
  - **Overall, no convincing evidence for return predictability**

Third PHD Topic: Co-movements in ASEAN stock markets

- **How do the correlations among ASEAN stock markets evolve over time?**

Previous studies:

- **Do not take account to the impact of market conditions.**
- **Do not measure the uncertainty of correlation (or the range of possible alternatives and contingencies).**
- **Do not pay attention to the impact of uncertainty of correlation.**

My study:

- **Better methodology: CWWB and DCC – GARCH (1,1)**
- **Measure the uncertainty of correlation using the difference between 97.5% and 2.5 % percentile of bootstrap correlation distribution.**
- **Take account to the impact of market conditions and uncertainty of correlation**

Third PHD Topic: Co-movements in ASEAN stock markets

- **Methodology: the wild bootstrap method (Mamen, 1993) and rolling window are applied to measured simple correlation while the DCC-MGARCH model (Engle, 2002) measures the conditional correlation.**
- **Data from 09/1999 to 11/2016 in 7 stock markets: Singapore, Thailand, Indonesia, Malaysia, Philippines, China and US.**
- **Results:**
    - **The correlations among ASEAN markets are higher around GFC & AEC**
    - **The correlations among ASEAN markets are higher compared to the ones between ASEAN markets and China, US.**
    - **The correlation uncertainty and market conditions wield a significant influence on the changes of correlations.**

What I want to do in the future?

- Apply Bayesian method in the process to improve return predictability
- Use credit analysis methods to build up credit level of companies and use it for predict stock returns / risk management.
- Measure sentiment of news to stocks and predict stock returns based on those indications.

THANK YOU FOR YOUR ATTENTION!