ETC3460 – Financial Econometrics

Project Presentation

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on behalf of **Group 40**

Sections

- Portfolio Stock Selection
- Portfolio Weighting Allocation
- Portfolio Return Time Series Properties
- Predictive Modelling
- Forecasts

Statistical Software used

- EViews 11
  - Used to observe the time series patterns

- R
  - *Majority of the work was done using R*
  - More flexible
  - Better functionality

Portfolio Stock Selection

1. Extracted **past one year's** close price data for all 200 stocks in the ASX200 index

2. Computed some basic (ex-post) statistical measures

- Four moments (Mean, Volatility, Skewness and Kurtosis)
- Sharpe Ratio (risk-adjusted return measure)
- CAPM alpha and beta

Note:

- Risk–free rate used = 0.000983% is the derived daily yield on the Australian 1-year government bond (applying the Effective Annual Rate formula reversely, assuming 252 trading days a year)
- Market return = Return on the ASX200 index

$$\text{Effective Annual Rate Formula} = \left(1 + \frac{r}{n}\right)^{n} - 1$$

Portfolio Stock Selection

- Filtered out stocks with Kurtosis > 6 (we don't want too many extreme values/outliers)
- Ranked the remaining stocks in terms of their Sharpe Ratio (we want good risk-adjusted returns)
- Selected the top 5 stocks

```
> asx200_stats %>%
+         filter(Kurtosis <= 6) %>%
+         arrange(-SharpeRatio)
# A tibble: 50 x 8
   ax_ticker      Mean  Stdev Skewness Kurtosis SharpeRatio   alpha  beta
   <fct>         <dbl>  <dbl>    <dbl>    <dbl>       <dbl>   <dbl> <dbl>
 1 PNV.AX    0.00294   0.0465  -0.798      3.24      0.0631 0.00420 1.53
 2 SLR.AX    0.00230   0.0416   0.167      3.34      0.0549 0.00317 1.06
 3 SPK.AX    0.000671  0.0161  -0.808      3.79      0.0412 0.00106 0.484
 4 FMG.AX    0.00111   0.0314  -0.309      1.96      0.0349 0.00190 0.971
 5 GOR.AX    0.00138   0.0417  -0.121      5.12      0.0328 0.00193 0.677
 6 SAR.AX    0.00117   0.0368   0.0428     4.29      0.0314 0.00172 0.679
 7 CNU.AX    0.000618  0.0201   0.154      2.23      0.0303 0.00118 0.697
 8 A2M.AX    0.000729  0.0247  -0.535      5.91      0.0291 0.00126 0.659
 9 ASB.AX    0.000823  0.0303  -0.453      5.32      0.0268 0.00180 1.19
10 PME.AX    0.000994  0.0392  -0.363      3.67      0.0251 0.00166 0.811
# ... with 40 more rows
```

- Polynovo Limited (PNV)
- Silver Lake Resources Limited (SLR)
- Spark New Zealand (SPK)
- Fortescue Metals Group Limited (FMG)
- Gold Road Resources Ltd (GOR)

<u>Diversification point of view</u>:

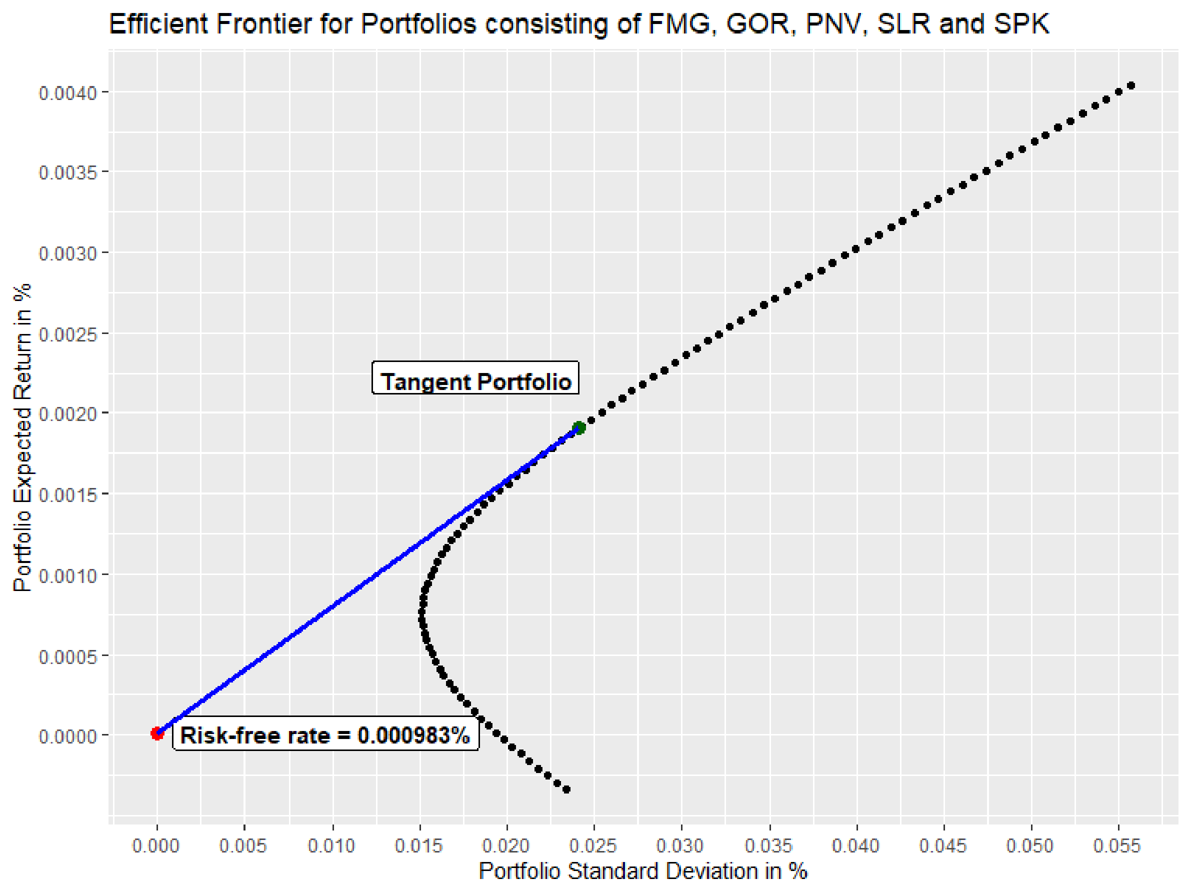
various industries: mining, materials, healthcare and telecommunication

Portfolio Weighting Allocation

- Constructed an **Efficient Frontier** based on the returns matrix and the variance-covariance matrix
- Selected the **tangent portfolio**
  - sits on the steepest Capital Allocation Line (CAL)
  - in other words, highest portfolio Sharpe ratio

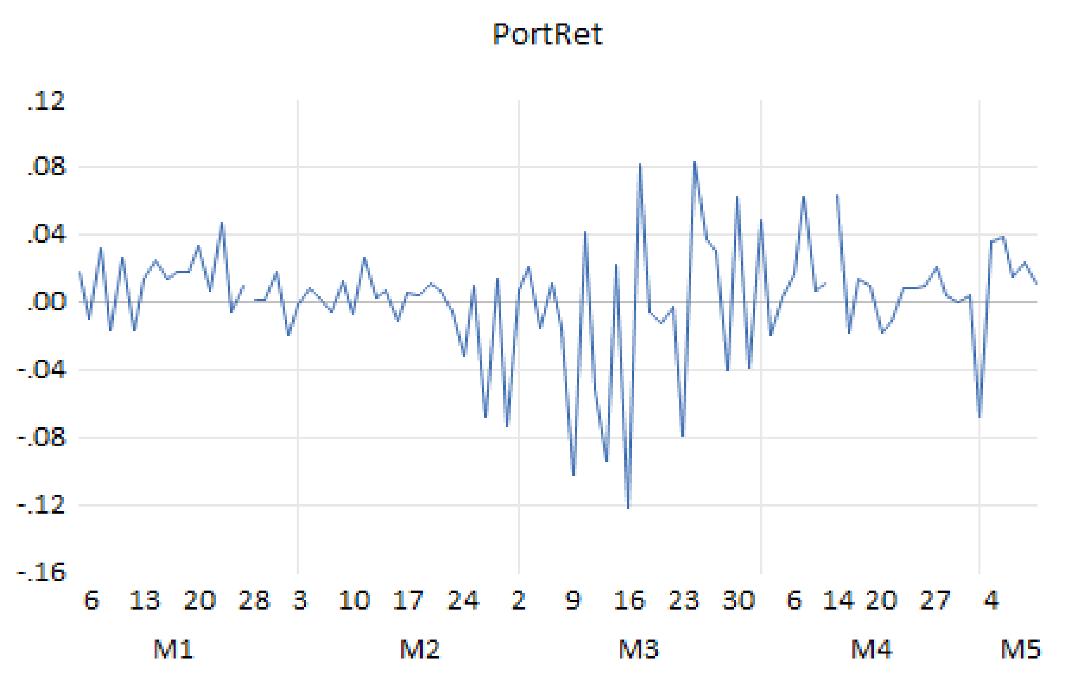
- Weightings of the tangent portfolio reported from R:

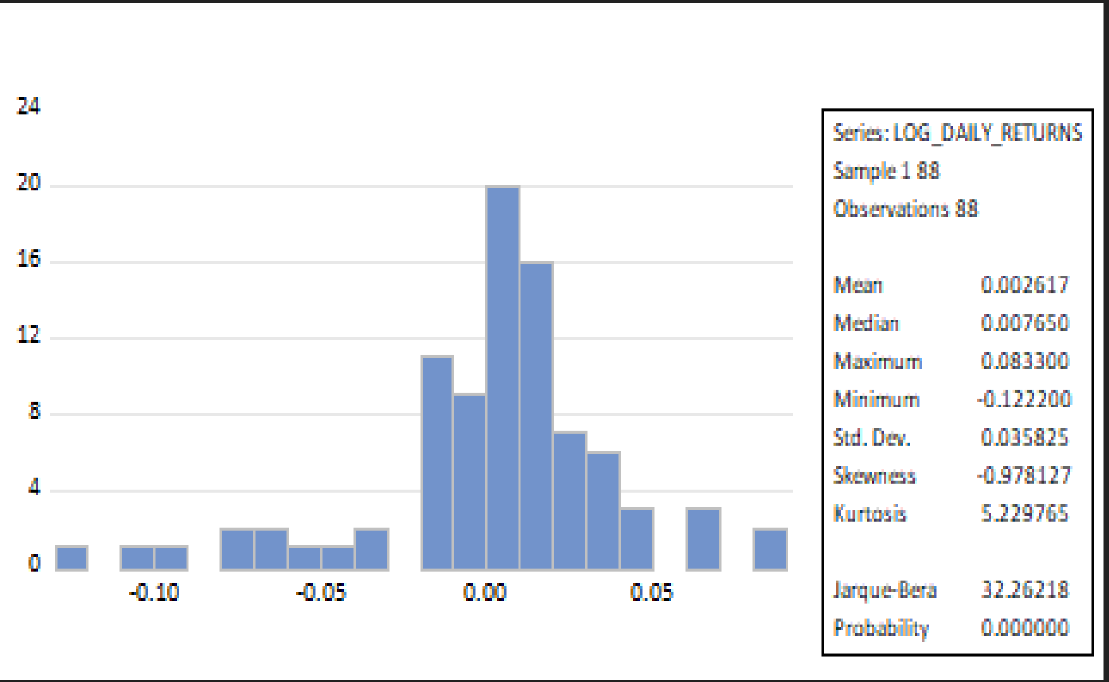
FMG	GOR	PNV	SLR	SPK
0.1097	*0.0283*	*0.3136*	*0.2805*	*0.2679*



Portfolio Return Time Series Properties

- Overall portfolio log-return (2020 Jan 3 – 2020 May 8): **23.01%**





Portfolio Return Time Series Properties

Constant Mean Model:

$$r_t = 0.002617 + u_t$$
$$(0.003819), N = 88$$

Serial Correlation ✓

Correlogram of Residuals

Date: 06/03/20 Time: 15:00
Sample: 1/03/2020 5/08/2020
Included observations: 88

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.268	-0.268	6.5276	0.011
		2	0.260	0.203	12.766	0.002
		3	0.086	0.220	13.453	0.004
		4	-0.091	-0.088	14.227	0.007
		5	0.251	0.155	20.219	0.001
		6	0.031	0.184	20.313	0.002
		7	-0.045	-0.103	20.507	0.005
		8	0.066	-0.098	20.942	0.007
		9	0.105	0.211	22.046	0.009
		10	0.013	0.081	22.062	0.015
		11	0.186	0.058	25.625	0.007
		12	-0.199	-0.195	29.768	0.003
		13	0.099	-0.020	30.795	0.004
		14	-0.072	-0.064	31.351	0.005
		15	0.053	0.021	31.658	0.007
		16	0.009	-0.017	31.667	0.011
		17	-0.114	-0.077	33.107	0.011
		18	0.059	0.028	33.505	0.014
		19	-0.130	-0.107	35.430	0.012
		20	0.079	-0.028	36.156	0.015

ARCH Effects ✓

Correlogram of Residuals Squared

Date: 06/03/20 Time: 15:17
Sample: 1/03/2020 5/08/2020
Included observations: 88

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.172	0.172	2.7000	0.100
		2	0.227	0.203	7.4349	0.024
		3	0.212	0.157	11.630	0.009
		4	0.034	-0.062	11.741	0.019
		5	0.407	0.371	27.512	0.000
		6	0.275	0.198	34.811	0.000
		7	0.015	-0.203	34.832	0.000
		8	0.106	-0.090	35.944	0.000
		9	0.079	0.131	36.578	0.000
		10	0.149	0.058	38.839	0.000
		11	0.281	0.057	46.965	0.000
		12	0.010	-0.081	46.975	0.000
		13	0.079	0.075	47.629	0.000
		14	-0.026	-0.134	47.703	0.000
		15	-0.054	-0.177	48.023	0.000
		16	0.016	-0.142	48.052	0.000
		17	-0.111	-0.084	49.425	0.000
		18	-0.042	0.034	49.624	0.000
		19	-0.031	0.045	49.734	0.000
		20	-0.142	-0.078	52.077	0.000

Predictive Modelling

- Main objective: **GOOD FORECASTS**
- Forecast accuracy (RMSE) > Model Fit (AIC)
- **Model Fitting**

1. pure ARMA models

- Automatic ARMA model selection using `ARIMA()` in *fable*
- Two best model fits (having the lowest AICc):

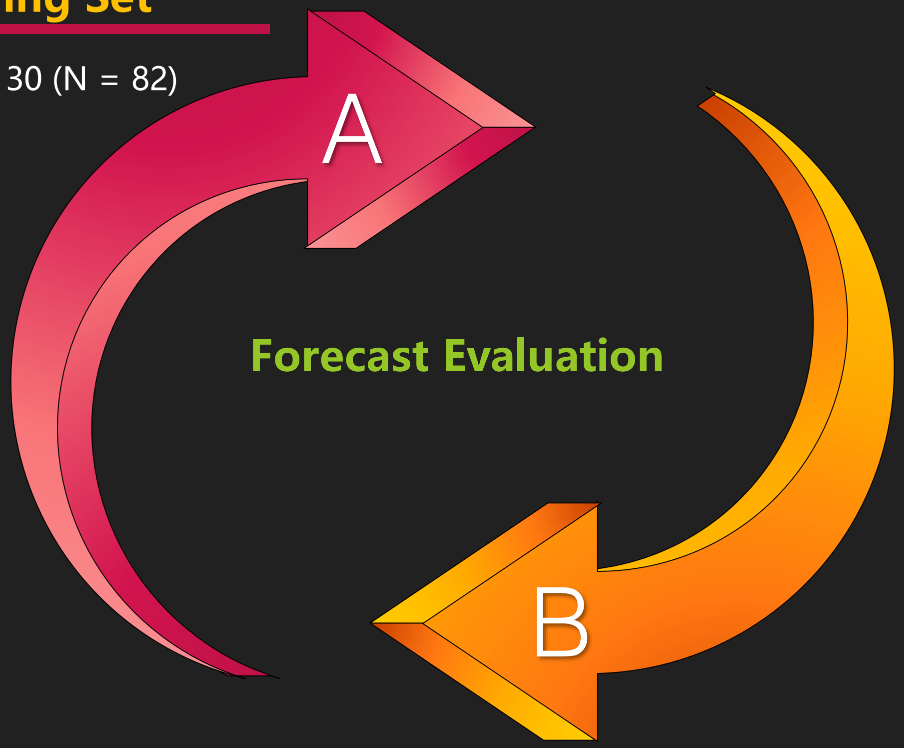
ARMA(2, 2)

MA(5)

- However, both pure ARMA models have ARCH effects in residuals
- We needed to add volatility modelling - GARCH and its variations

A **Training Set**

Jan 3 – April 30 (N = 82)



B **Test Set**

May 1 – May 8 (N = 6)

Predictive Modelling

rugarch v1.4-2

- **ARMA-GARCH Models** (GARCH models fitted using *rugarch* in R)
  - ARMA(2,2)-GARCH(1,1)
  - MA(5)-GARCH(1,1)
  - ARMA(2,2)-GARCH(2,1)
  - MA(5)-GARCH(2,1)
  - ARMA(2,2)-GARCH(1,2)
  - MA(5)-GARCH(1,2)

Model	RMSE
ARMA(2,2)-GARCH(1,2)	0.03687867
ARMA(2,2)-GARCH(1,1)	0.03687869
ARMA(2,2)-GARCH(2,1)	0.03700226
MA(5)-GARCH(1,2)	0.03720098
MA(5)-GARCH(1,1)	0.03720101
MA(5)-GARCH(2,1)	0.03785100

- Findings: ARMA(2,2) as the mean equation always had a better forecast accuracy than MA(5)
- Therefore, we dropped MA(5) and chose to use ARMA(2,2) as the mean equation going forward

Predictive Modelling

- **GARCH variations**
- ARMA(2,2)-GJRGARCH(1,1,1)
- ARMA(2,2)-EGARCH(1,1)
- Findings: EGARCH had a lower RMSE whereas GJRGARCH did even worse than the ordinary GARCH
- Therefore, we ruled out GJRGARCH

Model	RMSE
ARMA(2,2)-EGARCH(1,1)	0.03630688
ARMA(2,2)-GARCH(1,2)	0.03687867
ARMA(2,2)-GARCH(1,1)	0.03687869
ARMA(2,2)-GARCH(2,1)	0.03700226
ARMA(2,2)-GJRGARCH(1,1,1)	0.03704154

Predictive Modelling

rugarch v1.4-2

- **Adding CAPM**
- Dynamic regression model - CAPM with ARMA errors: CAPM-AR(1) (from `ARIMA()` in *fable*)
- ARMAX(2,2)-GARCH(1,1)
- ARMAX(2,2)-EGARCH(1,1)
- CAPM-GARCH(1,1)
- CAPM-EGARCH(1,1)

- Note:
- ASX200 index return was modelled by an automatically fitted ARMA model in *fable:* ARMA(1,2)
- "ARMAX" means that we include both the ARMA terms and the exogenous CAPM regressor (excess market return) in the mean equation

Predictive Modelling

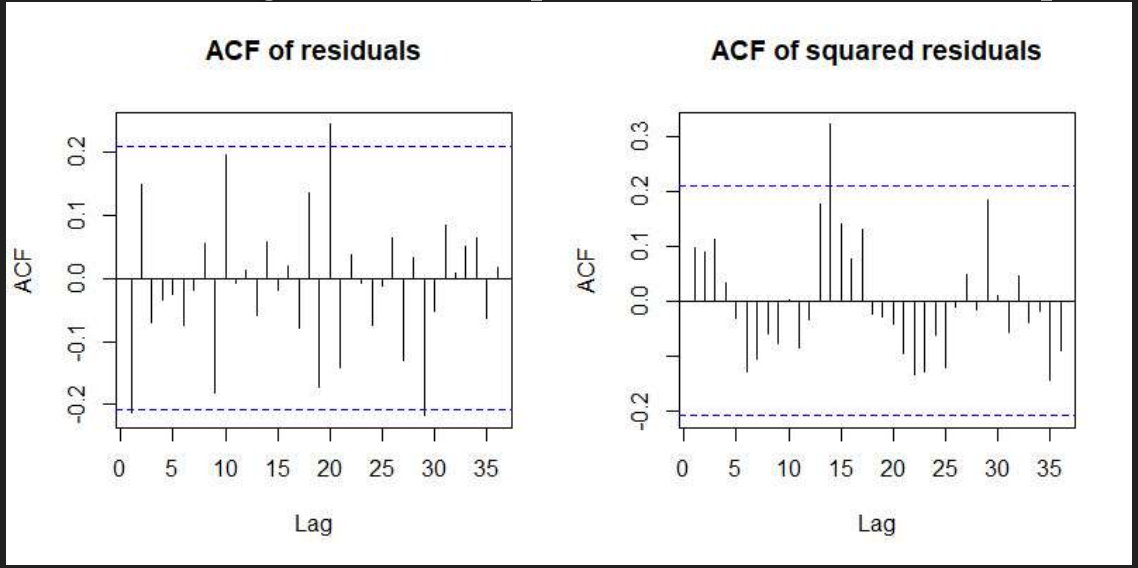
Final Model Selection

Portfolio Return CAPM-EGARCH(1,1): $r_t = 0.00413 + 1.0459 r_{m,t} + \varepsilon_t, \;\; \varepsilon_t = u_t \sigma_t, \;\; u_t \sim iid\ N(0,1)$

$$ln(\sigma_t^2) = -4.0604 + 0.9045(|u_{t-1}| - \mathbb{E}[|u_{t-1}|]) + 0.0063 u_{t-1} + 0.4907\ ln(\sigma_{t-1}^2)$$

ASX200 Index Return ARMA(1,2): $r_{m,t} = 0.4878 r_{m,t-1} - 0.8540 \varepsilon_{t-1} + 0.4921 \varepsilon_{t-2} + \varepsilon_t$

Residual Diagnostics (CAPM-EGARCH(1,1)):



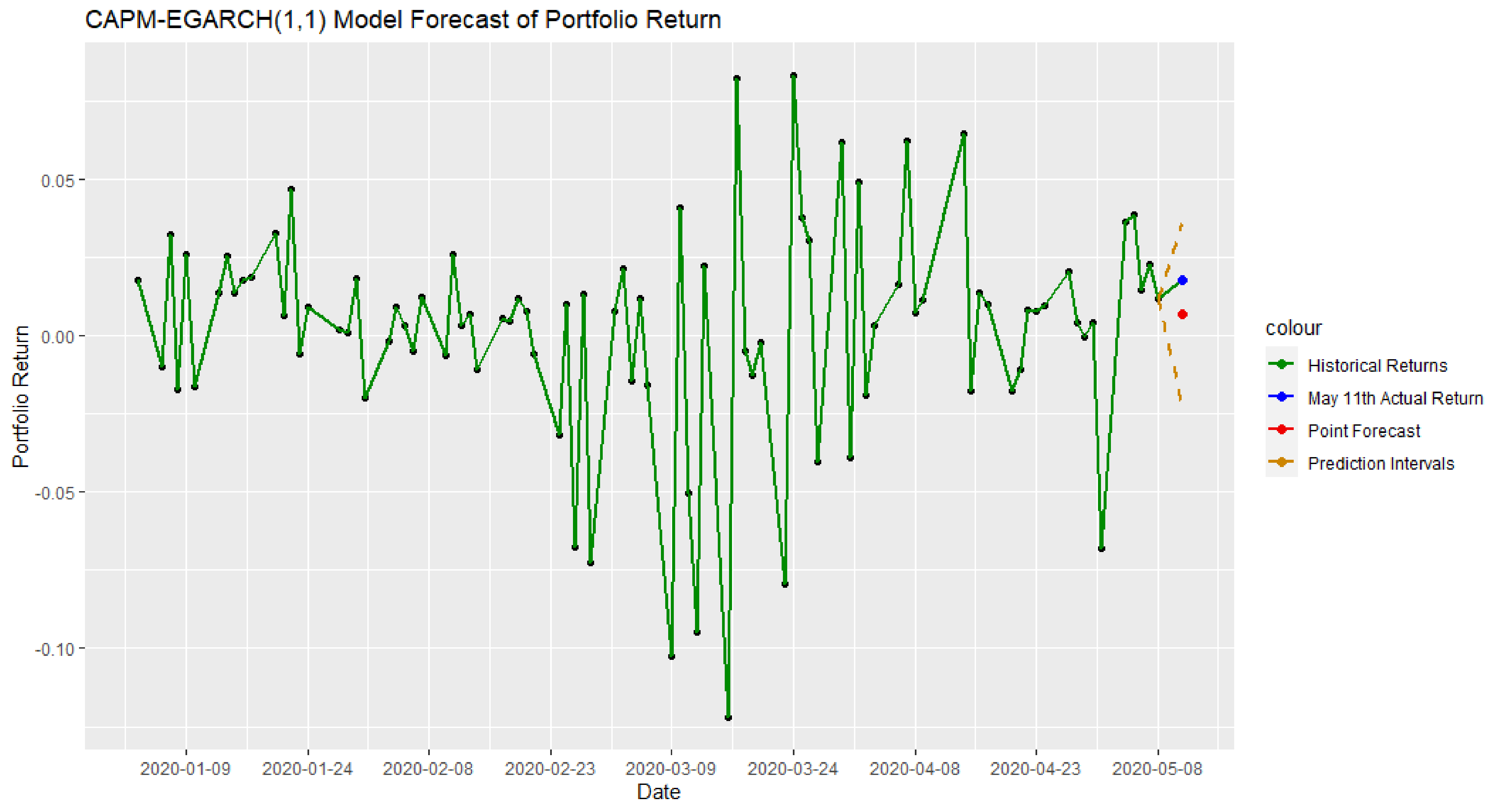
Model <chr>	RMSE <dbl>
CAPM-EGARCH(1,1)	0.03330253
CAPM-GARCH(1,1)	0.03333084
CAPM with AR(1) errors	0.03562929
ARMAX(2,2)-GARCH(1,1)	0.03567486
ARMAX(2,2)-EGARCH(1,1)	0.03580940
ARMA(2,2)-EGARCH(1,1)	0.03630688
ARMA(2,2)-GARCH(1,2)	0.03687867
ARMA(2,2)-GARCH(1,1)	0.03687869
ARMA(2,2)-GARCH(2,1)	0.03700226
ARMA(2,2)-GJRGARCH(1,1,1)	0.03704154
MA(5)-GARCH(1,2)	0.03720098
MA(5)-GARCH(1,1)	0.03720101
MA(5)-GARCH(2,1)	0.03785100

Forecasts

- **Forecasts**
- One-step Point Forecast on the ASX200 index return: 0.2506%
- One-step Point Forecast on the Portfolio Return: **0.6749%**
- One-step 95% Prediction Interval: **[-2.2625%, 3.6123%]**
- 5% Conditional Value at Risk (CVaR): **-1.7902%**

- Actual Portfolio Return on May 11th : **1.79%**

Forecasts



CAPM-EGARCH(1,1) Model Forecast of Portfolio Return
Portfolio Return
0.05
0.00
-0.05
-0.10
2020-01-09
2020-01-24
2020-02-08
2020-02-23
2020-03-09
2020-03-24
2020-04-08
2020-04-23
2020-05-08
Date
colour
Historical Returns
May 11th Actual Return
Point Forecast
Prediction Intervals

Forecasts

$$r_t = 0.002617 + u_t$$
$$(0.003819), N = 88$$

- Comparing with a benchmark model – constant mean model:
- Point forecast from the constant mean model: 0.2617%
- 95% prediction interval: [-6.8579%, 7.3813%]

- Conclusion: our CAPM-EGARCH(1,1) model has a <u>more accurate point forecast</u> and <u>a much narrower interval forecast</u>.

THANK YOU.

by George Wang – Group 40.