Active Portfolio Managment

Bernt Arne Ødegaard

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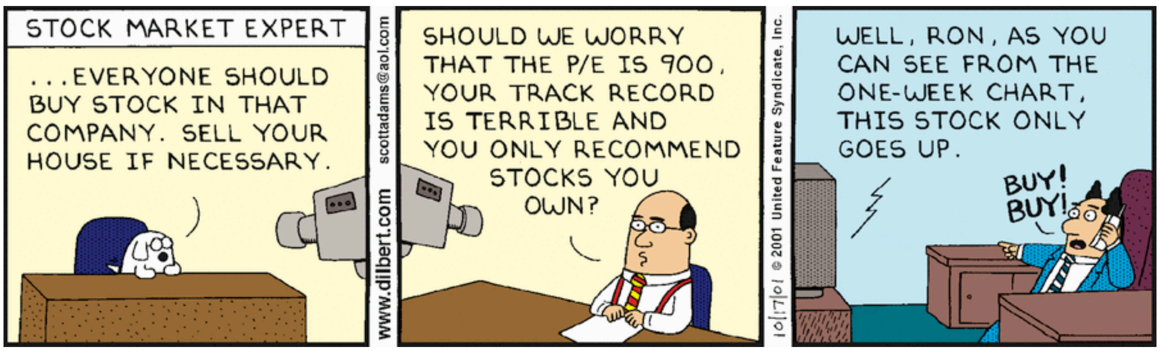


1 Overview of lecture

Perspective – Sharpe's fundamental law
What are ways in which investment managers are *active*?
Premise: Forecasting ability

- Selection
  - Treynor-Black
  - Black-Litterman
- Timing

2 Introduction

Hard to define what is an *active* portfolio.
A common way of thinking is that it is a portfolio that deviates from a passive investment strategy, such as an index fund, or fixed weights equity/fixed income.
Necessary condition for trying an active strategy:
Forecasting ability

- in the time dimension (market timing), or
- in the crossection (asset selection).

For active strategies to generate superior performance must either be able to

- forecast future performance, choose asset with the highest expected return, or
- identify mispricing (alpha) in crossection. Buy underpriced stock/sell overpriced stock.

3 Theory

Often quoted starting point: Sharpe (1991)'s famous "arithmetic of active management":

> "it must be the case that
> (1) before costs, the return on the average actively managed dollar will equal the return on the average passively managed dollar, and
> (2) after costs, the return on the average actively managed dollar will be less...
> These assertions will hold for any time period. Moreover, they depend only on the laws of addition, subtraction, multiplication and division. Nothing else is required."

However, Pedersen (2018) arguest that this is a too pessimistic view. It presumes that this is a zero-sum game. For example, Pedersen (2018) argues that the service of financiers to e.g. add to traded assets by doing IPO's, and other financial engineering, adds value to the market, making it a positive sum game.

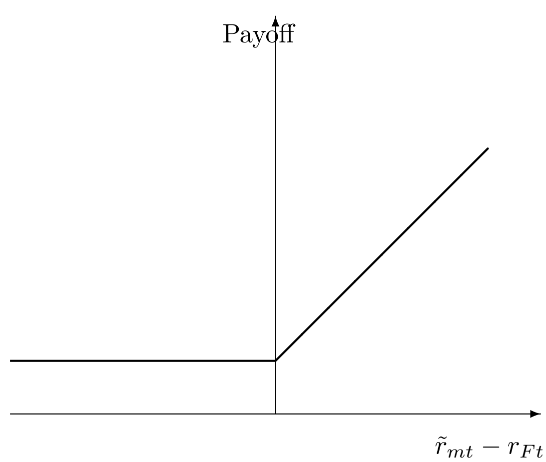
4 Market Timing

Market Timing. Switch from the market to the risk free asset if you think $E[\tilde{r}_{mt} < r_{Ft}]$, and the other way if $E[\tilde{r}_{mt} > r_{Ft}]$.

How will you determine whether your forecasting ability actually generates performance?

What is special about the payoff on a market timers portfolio?

Take the extreme case. What if the portfolio manager is always correct. He knows when $r_{mt} > r_{Ft}$ and $r_{mt} < r_{Ft}$. Then, if $r_{mt} > r_{Ft}$ he invests 100% in market, otherwise, if $r_{mt} < r_{Ft}$, he invests 100% in r_F.



This is the payoff on a call option on the market with exercise price $r_m = r_f$. So, the value of the timing ability equals the cost of a call option on the market. (an index option).

Timing ability: Ability to create a call option that costs less than the one offered in the market.

How do you measure superior timing ability? Notice that the payoff on the market timer's portfolio is a nonlinear function of the excess return on the market.

Run regressions of the general form:

$$r_p - r_f = \alpha_p + \beta_p(r_m - r_f) - \gamma_p min(0, r_m - r_f) + \epsilon_p$$

We conclude that there is timing ability if $\gamma_p > 0$.
(See performance measurement lecture for other regression specifications).

5 Selection in the market model

To illustrate selection we conside selection in the context of the market model.
Recall the model:

$$\tilde{r}_i = \alpha_i + \beta_i \tilde{r}_m + \tilde{\varepsilon}_i$$

If a stock is priced correctly, $\alpha_i = 0$.

$$\beta_m = 1$$

Errors uncorrelated across assets

$$\mathrm{cov}(\varepsilon_i, \varepsilon_j) = 0 \ \ \forall \ i \neq j$$

For a portfolio of n stocks, need to estimate $3n + 2$ parameters.
$(\alpha_i, \beta_i, \sigma_i + \sigma_m, E[r_m - r_f]$
An analyst will in this framework provide estimates of α_i. For a given stock, if the alpha (α_i) is different from zero, will use that to take active positions.
$\alpha_i < 0$: Sell
$\alpha_i > 0$: Buy

This is the setting of the **Treynor-Black** model, which provides a recipe for creating a portfolio reflecting the views given by the alpha estimates (Bodie, Kane, and Marcus, 2021)

1. Macroeconomic analysis is used to estimate the risk premium and risk of the market index.
2. Statistical analysis is used to estimate the beta coefficients of all securities and their residual variances, $\sigma^2(e_i)$.
3. The portfolio manager uses the estimates for the market model risk premium and the individual betas to find the expected return *absent* any contribution from security analysis
4. Security specific alphas are found using security valuation models (stock pricing). These alphas *summarize* the additional premium due to the private information (the stock valuation)

Armed with thesee alphas there is an optimization procedure (Bodie et al., 2021)

1. Compute the initial postion of each security in the active portfolio as $w_i^0 = \frac{\alpha_i}{\sigma^2(e_i)}$.
2. Scale those initial positions to force portfolio weights to sum to one by dividing by their sum, that is $w_i = \frac{w_i^0}{\sum_i w_i^0}$.
3. Compute the alpha of the active portfolio $\alpha_A = \sum_i w_i \alpha_i$.
4. Compute the residual variance of the active portfolio $\sigma^2(e_A) = \left[\frac{\alpha_A/\sigma^2(e_A)}{E[r_m]/\sigma_m^2}\right]$.
5. Compute the beta of the active portfolio $\beta_A = \sum_i w_i \beta_i$.

6. Adjust the initial position in the active portfolio $w_A^* = \frac{w_A^0}{1+(1-\beta_A)w_A^0}$
7. Note the optimal risky portfolio now has weights $w_m^* = 1 - w_A^*; w_i^* = w_A^* w_i$.
8. Calculate the risk premium of the optimal risky portfolio from the risk premium of the index portfolio and the alpha of the active portfolio.

$$E[R_p] = (w_m^* + w_A^*)\, E[R_M) + w_A^* \alpha_A$$

Notice that the beta of the risky portfolio is $w_m^* + w_A^* \beta_A$ because the beta of the index portfolio is 1.

9. Compute the variance of the optimal risky portfolio from the variance of the index portfolio and the residual variance of the active portfolio.

$$\sigma_P^2 = (w_m^* + w_A^* \beta_A)^2 \sigma_m^2 + (w_A^* \sigma(e_A))^2$$

Exercise 1.

We consider an active portfolio calculation example that corresponds to an example in Chapter 8 of Bodie, Kane and Marcus.

Use the S&P 500 as a market index. Consider the six stocks Walmart(WMT),Target (TGT), VeriZon (VZ), AT&T(T), Ford(F), General Motors(GM).

Using monthly returns for the period after 2010, estimate the parameters of the Market Model.

Solution to Exercise 1.

Market model regressions

$$er_i = \alpha_i + \beta_i er_m + \varepsilon_i$$

Show R code

Preparatory

```
first_date <- as.Date("2010-01-01")
tickers <- c("WMT","TGT","VZ","T","F", "GM")
companies <- c("Walmart","Target","VeriZon","ATT","Ford", "GM")
```

Get data

Step 1 Risk free rate

```
treas_1m <- getSymbols("DGS1MO", src="FRED", auto.assign=FALSE)
names(treas_1m) <- "treas_1m"
treas_1m <- na.omit(treas_1m)
                                            # pick last observation in a given month
Rf <- treas_1m[endpoints(treas_1m,"month"),]
names(Rf) <- "Rf"
Rf <- Rf/1200                               # don't want annualized percentage interest rates, straig
index(Rf) <- as.yearmon(index(Rf))
Rf <- na.omit(lag(Rf,1))  # that last observation should be matched with returns the next month
Rf <- window(Rf, start=as.yearmon(first_date))
```

Step 2 Excess Stock returns. Create a function that takes care of the subtraction of the risk free rate

```
get_stock_excess_returns <- function(ticker){
    data <- getSymbols(ticker,auto.assign=FALSE,from=first_date)
    daily_prices <-na.omit(data[,6])
    monthly_returns <- monthlyReturn(daily_prices)
    names(monthly_returns) <- "monthly_returns"
    index(monthly_returns) <- as.yearmon(index(monthly_returns))
    data <- merge(monthly_returns,Rf,all=FALSE)
```

```
    excess_returns <- data$monthly_returns-data$Rf
    names(excess_returns) <- "excess_returns"
    return(excess_returns)
}
                                    # use the SP500 as market index
ticker <- "^GSPC"
erm <- get_stock_excess_returns(ticker)
names(erm) <- "erm"
summary(erm)
                                    # Walmart
ticker <- "WMT"
erWMT <- get_stock_excess_returns(ticker)
names(erWMT) <- "erWMT"
```

(The other stocks are similar)

Step 3 Run regressions

```
data     <- merge(erWMT, erm , all=FALSE)
regrWMT <- lm(data$erWMT~data$erm)
```

(The others similar)

	Dependent variable:					
	erWMT	erTGT	erVZ	erT	erF	erGM
	(1)	(2)	(3)	(4)	(5)	(6)
erm	0.469***	0.842***	0.444***	0.588***	1.437***	1.454***
	(0.086)	(0.126)	(0.085)	(0.089)	(0.139)	(0.140)
Constant	0.005	0.005	0.002	0.001	−0.003	−0.006
	(0.004)	(0.005)	(0.004)	(0.004)	(0.006)	(0.006)
Observations	159	159	159	159	159	149
Adjusted R^2	0.153	0.217	0.144	0.211	0.401	0.420
Residual Std. Error	0.046	0.068	0.046	0.048	0.075	0.071
Note:				*p<0.1; **p<0.05; ***p<0.01		

Calculate

- SD excess return
- Beta
- Systematic risk $\beta_i \sigma_m$
- Unsystematic risk
- Correlation with market

Show calculations for the market and the first company (Walmart)

```
# table like panel A
tab <- matrix(nrow=7,ncol=5)
rownames(tab) <- c("index",companies)
colnames(tab) <- c("sd excess ret","beta","syst","SD residual","corr w mkt ")
                                    #market
sigmaM <- sd(erm)
tab[1,1] <- sigmaM
tab[1,2] <- 1
tab[1,3] <- sigmaM
tab[1,4] <- 0
tab[1,5] <- 1
```

```r
#walmart
sdretWMT  <- sd(erWMT)
alphaWMT  <- regrWMT$coefficients[1]
betaWMT   <- regrWMT$coefficients[2]
resWMT    <- regrWMT$residuals
sigmaWMT  <- sd(resWMT)
corWMTm   <- cor(erWMT, erm)
tab[2,1] <- sdretWMT
tab[2,2] <- betaWMT
tab[2,3] <- betaWMT*sigmaM
tab[2,4] <- sigmaWMT
tab[2,5] <- corWMTm
```

	sd excess ret	beta	syst	SD residual	corr w mkt
index	0.0429	1.0000	0.0429	0.0000	1.0000
Walmart	0.0505	0.4688	0.0201	0.0463	0.3983
Target	0.0768	0.8416	0.0361	0.0677	0.4707
VeriZon	0.0493	0.4444	0.0191	0.0455	0.3866
ATT	0.0543	0.5879	0.0252	0.0481	0.4648
Ford	0.0970	1.4372	0.0617	0.0749	0.6360
GM	0.0933	1.4536	0.0624	0.0708	0.6511

```r
# table like panel B
data <- merge(resWMT,
              resTGT,
              resVZ,
              resT,
              resF,
              resGM)
colnames(data) <- companies
corr <- cor(data, use="pairwise.complete.obs")
corr[upper.tri(corr, diag=TRUE)]<-NA
print(corr)
filename <- paste0(outdir, "correlations_residuals.tex")
xt <- xtable(corr[2:6,], digits=3)
print(xt, file=filename, floating=FALSE)
```

Calculating some descriptive statistics

```r
data      <- merge(erWMT, erTGT, erVZ, erT, erF, erGM, erm, all=FALSE)
desc_stats <- matrix(nrow=6, ncol=7)
colnames (desc_stats) <- c(companies, "SP500")
rownames (desc_stats) <- c("mean", "sd", "min", "med", "max", "n")
desc_stats[1,] <- colMeans(data)
desc_stats[2,] <- apply(data, 2, sd)
desc_stats[3,] <- apply(data, 2, min)
desc_stats[4,] <- apply(data, 2, median)
desc_stats[5,] <- apply(data, 2, max)
desc_stats[6,] <- apply(data, 2, length)
```

	Walmart	Target	VeriZon	ATT	Ford	GM	SP500
mean	0.009	0.012	0.005	0.006	0.007	0.007	0.008
sd	0.051	0.078	0.048	0.054	0.095	0.093	0.042
min	-0.157	-0.289	-0.118	-0.174	-0.307	-0.312	-0.126
med	0.008	0.006	0.003	0.001	-0.002	0.003	0.013
max	0.148	0.247	0.118	0.207	0.319	0.281	0.127
n	149	149	149	149	149	149	149

6 Summarizing – active portfolio management

- Perspective – Sharpe's fundamental law
- Premise of active management: Forecasting, either in time or the crossection.
- Timing: Switching between asset classes based on expected return forecasts.
- Selection: "Stock picing" Over/Underpriced assets

References

Zvi Bodie, Alex Kane, and Alan J Marcus. *Investments*. McGraw Hill/Irwin, 12 edition, 2021.

Lasse Heje Pedersen. Sharpening the arithmetic of active management. *Financial Analyst Journal*, 74(1):21–36, 2018.

William F Sharpe. The arithmetic of active management. *Financial Analysts Journal*, 47(1):7–9, 1991.