Active Portfolio Management

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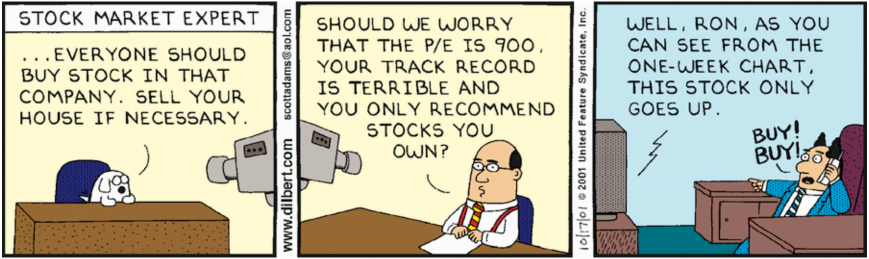
April 18, 2023



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

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).

Introduction

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.

Theory

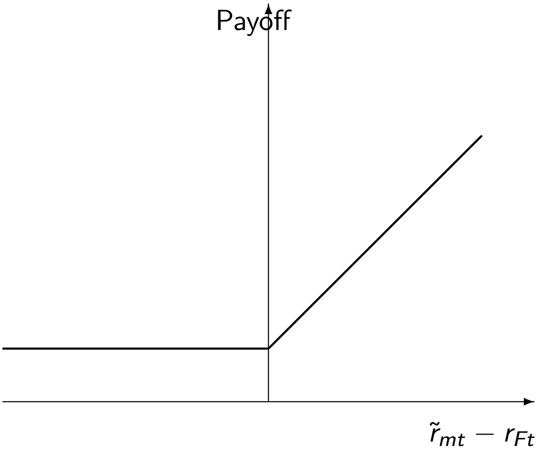
Often quoted starting point: Sharpe (1991)'s famous "arithmetic of active management":

> *"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.

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.



Payoff on a call option on the market with exercise price $r_m = r_f$.

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).

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

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

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)

Optimization procedure

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

- Compute the initial postion of each security in the active portfolio as

$$w_i^0 = \frac{\alpha_i}{\sigma^2(e_i)}$$

- Scale those initial positions to force portfolio weights to sum to one by dividing by their sum, that is

$$w_i = \frac{w_i^0}{\sum_i w_i^0}$$

- Compute the alpha of the active portfolio

$$\alpha_A = \sum_i w_i \alpha_i$$

- Compute the residual variance of the active portfolio

$$\sigma^2(e_A) = \left[\frac{\alpha_A / \sigma^2(e_A)}{E[r_m]/\sigma_m^2} \right]$$

Optimization procedure

- Adjust the initial position in the active portfolio

$$w_A^* = \frac{w_A^0}{1 + (1 - \beta_A) w_A^0}$$

- Note the optimal risky portfolio now has weights

$$w_m^* = 1 - w_A^*; w_i^* = w_A^* w_i$$

- 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.

- 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

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.

Exercise

Doing Market model regressions and calculate the various paramters

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

Exercise

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","
```

Exercise - get risk free rate

```
treas_1m <- getSymbols("DGS1MO", src="FRED", auto.assign
names(treas_1m) <- "treas_1m"
treas_1m <- na.omit(treas_1m)
Rf <- treas_1m[endpoints(treas_1m,"month"),]
names(Rf) <- "Rf"
Rf <- Rf/1200   # translate from annualized percentages
index(Rf) <- as.yearmon(index(Rf))
Rf <- na.omit(lag(Rf,1))
Rf <- window(Rf,start=as.yearmon(first_date))
```

Exercise - get stock returns

```
get_stock_excess_returns <- function(ticker){
    data <- getSymbols(ticker,auto.assign=FALSE,from=fir
    daily_prices <-na.omit(data[,6])
    monthly_returns <- monthlyReturn(daily_prices)
    names(monthly_returns) <- "monthly_returns"
    index(monthly_returns) <- as.yearmon(index(monthly_r
    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 in
ticker <- "^GSPC"
erm <- get_stock_excess_returns(ticker)
names(erm) <- "erm"
ticker <- "WMT"                                # Walmart
erWMT <- get_stock_excess_returns(ticker)
names(erWMT) <- "erWMT"
```

Exercise – Desc stats

```
data       <- merge(erWMT,erTGT,erVZ,erT,erF,erGM,erm,
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)
```

Exercise – Desc stats

	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

Exercise – Run regressions

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

Exercise – Market model regressions

	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

Exercise – Market model parameters

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

Exercise – Market model parameters

```
tab <- matrix(nrow=7,ncol=5)
rownames(tab) <- c("index",companies)
colnames(tab) <- c("sd excess ret","beta","syst","SI
                                              #market
sigmaM <- sd(erm)
tab[1,1] <- sigmaM
tab[1,2] <- 1
tab[1,3] <- sigmaM
tab[1,4] <- 0
tab[1,5] <- 1
```

Exercise – Market model parameters

```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
```

Exercise – Market model parameters

	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

Correlations between residuals

```r
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
filename <- paste0(outdir,"correlations_residuals.t
xt <- xtable(corr[2:6,],digits=3)
print(xt,file=filename,floating=FALSE)
```

Correlations between residuals

	Walmart	Target	VeriZon	ATT	Ford	GM
Target	0.358					
VeriZon	0.165	-0.067				
ATT	0.023	-0.029	0.523			
Ford	-0.029	0.099	-0.224	-0.126		
GM	-0.076	0.096	-0.221	-0.055	0.644	

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

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.