U.S. FUNDAMENTAL

Equity Risk Model

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U.S. Fundamental Equity Risk Model

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Introduction

The Northfield Fundamental Model is a multi-factor risk model designed to help US equity managers control portfolio exposure to endogenous factors such as price-to-earnings ratios and yield. It is a relaxed CAPM construct: while acknowledging the importance of Beta in measuring the risk of a portfolio, it goes further to include other variables in capturing sources of covariance between securities. The model is based on 67 factors (66 plus Beta), 55 of which are industry dummy variables. It is fully compatible with the Northfield Open Optimizer.

This booklet introduces the model with a short discussion of the basic concepts underlying the risk model, followed by a description of the process by which the model is estimated. A list of the factors used in the Northfield Fundamental Model, their definitions, and means by which they are derived is also included. The structure of the data file, where the coefficients of the model are stored, is shown at the end.

Basic Concepts

Risk and Return

The positive relationship between risk and expected return is one of the most basic concepts of investment theory. Modern portfolio theory says, however, that only that risk which is undiversifiable in aggregate should increase expected return. The risk associated with any investment can be broken into two parts: the idiosyncratic (or unsystematic) risk, which is diversifiable, and the systematic risk, which may not be diversifiable.

Idiosyncratic Risk

The idiosyncratic risk associated with a holding in any one security is the risk that is particular to that one investment. If the investment is common stock, idiosyncratic risk can come from management decisions, or anything else that changes the fortunes of one company but does not affect the fortunes of other companies.

Systematic Risk

Systematic risk arises from factors which affect the returns of virtually all securities in the market. For example, a rise in the level of interest rates will increase bond yields, thus providing investors with an alternative investment vehicle to equities. This, in turn, will lower the demand for stocks, and, *ceteris paribus*, drive the prices of stocks down.

Diversification of Risk

Idiosyncratic risk (security specific) can be diversified away simply by having many different securities in a portfolio. For example, which is the winner in a lawsuit brought by one corporation against another is a risk that ordinarily is borne only by the investors in one company or the other and is therefore a specific, or unsystematic risk. That risk does not manifest itself for the entire portfolio; the wealth of all investors together will not be affected by which company wins the lawsuit, since the other company must pay what the first company wins. A portfolio that bears this risk should not be expected to earn extra return from bearing the risk of the lawsuit, because the risk may be diversified away by buying stock in both companies. The portfolio that includes only one of those companies is therefore an inefficient bearer of risk; that is, it is bearing risk without being compensated for that risk. Theoretically, the net risk that any one investment contributes to a well-diversified portfolio may be measured by the covariance of the investment's return with the return on the market portfolio. This risk is usually expressed as Beta, where the Beta of an investment is equal to the covariance of the investments returns with the markets returns, divided by the variance of the market returns.[1]

Multiple Factor Models

A more complex way to measure portfolio risk than using a single index (Beta) is to apply many factors to estimate portfolio risk. In this framework return and risk are measured by a portfolio's exposure to multiple factors. There are several advantages of using multiple factor models over a single-index model.

- Economic logic is used in the development of multiple-factor models and selecting the appropriate factors, these models are not purely dependent on historical relationships.
- Multiple factor models allow for a more thorough understanding of a portfolio's exposure to different variables.
- Multiple factor models allow for analyses that are more precise, and lead to better-informed investment decisions.
- Multiple factor models are better equipped to deal with outliers.

Mathematically, a multiple factor model can be expressed as follows:

$$r_i = b_{i,1}\, f_1 + \cdots + b_{i,n}\, f_n + e_i$$

where

r_i = the return over the risk-free rate for company i
$b_{i,n}$ = the price of factor n (the risk premium) for company i
f_n = the value of factor n
e_i = the stock-specific return for company i

By describing each company's risk and return using a specific number of factors, the calculation of expected portfolio return and risk is greatly simplified. The covariance matrix of all of the factors, and the securities' exposures to them can be used to estimate the expected return and variance of a portfolio.[2]

[1] For more about this topic, refer to chapter 2 of Rudd, Andrew and Henry K. Clasing, Jr., Modern Portfolio Theory: The Principles of Investment Management, Orinda, CA, Andrew Rudd, 1988.

[2] For a more complete discussion of this topic, please refer to Rosenberg, Barr, "Extra-Market Components of Covariance in Securities Markets," Journal of Financial and Quantitative Analysis, March 1974, pp. 263-274. Edwin J. Elton and Gruber, Martin J., Modern Portfolio Theory and Investment Analysis, New York, John Wiley & Sons, Inc., 1991, Chapter 6 also deals with this subject matter.

Model Overview

Basics

The Northfield US Fundamental Equity Risk Model uses security and company characteristics (such as P/E or industry classification) that are observable about each security to gauge the level of similarity between two stocks and hence their likely degree of covariance. It is an endogenous multiple factor model of the behavior of US common stocks.

The dataset for the Fundamental model provides information on approximately 5000 US companies including several hundred major ADRs. The model estimation is done at month end. The modeling process that estimates the return to each factor each (monthly) period uses a subset of the universe consisting of firms with market capitalization of more than $250 million. The resulting estimation universe consists of approximately the largest 3000 firms (as of March 2013). Historical data sets are available for each month starting with January of 1989.

Description of the Fundamental Model

The Northfield Fundamental Model is a relaxed CAPM construct; it is based on the premise that securities are all correlated with the general market, a relationship which is measured by the famous Beta. It also acknowledges, however, that certain groups of securities have covariances that are not related to CAPM Beta. This extra-market covariance is captured in our model using the exposure of each stock to 66 factors: 11 fundamental company variables (endogenous variables) and 55 industries. These factors are used twice: once to estimate each stock's Beta, and another time to estimate its alpha.

The Fundamental Factor Model explains the covariance among US stock returns. It is assumed that beta can explain some but not all of the structure of the covariance. For a detailed derivation, see Rosenberg and Guy (*Financial Analyst Journal*, 1976). There are sixty-seven factors (items of commonality). The sixty-seven factors consist of beta, eleven fundamental company characteristics, and fifty-five industry groups. The model can be written as:

$$r_i = r_f + \beta_i(r_m - r_f) + \sum_{k=1}^{66} E_{i,k}\, a_k + \varepsilon_i \tag{1}$$

r_i = return on stock i during period t
r_f = risk free rate of return during period t (three month Treasury bill)
r_m = return on the market (our reference universe) during period t
β_i = market beta of stock i at time t
$E_{i,k}$ = exposure of stock i to factor k at time t
exposures are standardized values of continuous variables such as yield
dummy variables for industry membership
a_k = Jensen's alpha associated with factor k during period t
ε_i = error term associated with stock i during period t

Essentially, it is nothing more than a standard CAPM with an effort made to sub-divide the alpha term into 66 components. To the extent we can associate portions of alpha to common factors we increase the ability of the model to explain covariance, unlike the simple CAPM, which assumes that beta alone explains all covariance among securities.

Estimation

The model is estimated each month in two steps: 1-builds a beta forecast from company fundamentals, 2-infers returns to the factors.

The starting point for both is a preliminary beta estimate for each stock. As in traditional CAPM, each stock's (60 month) time series of returns is regressed against the market return.

$$r_{i,t} = r_{f,t} + \hat{\beta}_i(r_{m,t} - r_{f,t}) + \varepsilon_{i,t} \quad t = 1 \dots 60 \tag{2}$$

β_i = time series estimate of beta on stock i
$\varepsilon_{I,t}$ = error term for stock i during period t

To account for the tendency of beta to shift toward one over time, we then apply the method of Blume (*Journal of Finance*, June 1975).

$$\beta_i^* = C\beta_i + K \tag{3}$$

C, K = constants

This is the preliminary beta estimate.

Beta from Fundamentals

To improve the quality of fit of the model, we allow the beta values for each stock to vary over time. For example, it can be observed that highly levered companies (high debt to equity ratios) have higher beta values. We could then imagine that a company that has just taken on a great deal of debt to finance an acquisition would have its beta increase. To capture the changes in beta values over time for a given company, we start by using a cross-sectional regression to estimate the relationships between beta values and company characteristics across the universe.

$$\beta_i^* = \sum_{k=1}^{66} E_{i,k}\hat{b}_k + \delta_i \quad i = 1 \dots 3000 \tag{4}$$

$E_{i,k}$ = exposure of stock i to characteristic k at time t (observable)

b_k = sensitivity of beta values with respect to differences from stock to stock in exposure to fundamental characteristic k at time t

δ_i = error term for the beta of stock i at time t

We assume then that the b_k values that are derived from an analysis across the universe of companies can then be applied to a single company as its characteristics change through time. This gives a contemporaneous estimate for β_i.

$$\beta_i^{\text{contemporaneous fundamentals}} = \sum_{k=1}^{66} E_{i,k} b_k \quad (5)$$

Incidentally, this rather complicated procedure for getting a beta has one additional benefit. We can get a reasonable estimate of beta for a stock with no return history, such as an initial public offering. Even though it has no return history, fundamental characteristics such as P/E, yield, and industry are immediately observable and equation (5) can still be used.

Factor Alphas

To estimate returns to the factors, we plug the preliminary beta values into equation (1) and run a cross-sectional regression[3].

$$r_i = r_f + \beta_i(r_m - r_f) + \sum_{k=1}^{66} E_{i,k}\,\hat{a}_k + \varepsilon_i \quad i = 1 \dots 3000 \quad (6)$$

The observations in all cross-sectional regressions are weighted by square root of market capitalization, which compensates for the skewness in the distribution of market capitalization. If the observations are equally weighted, the analysis is biased toward small capitalization names that are far more numerous. If the observations are purely capitalization weighted, the effective number of observations gets far too small for the large number of independent variables. This procedure provides essentially the same result as generalized-least squared methods that weight observations by inverse error terms (see Grinold and Kahn, Active Portfolio Management, 1st Edition, footnote #9, pg. 59). Each coefficient represents the amount of return associated with a unit exposure to a factor.[4]

As previously noted, the estimation of factor returns is done on a reference universe of all US common stocks with more than $250 million market capitalization. The return on the market portfolio is the return on this subset portfolio. This return computation is weighted by square root of market capitalization of the members.

Once we have the periodic returns to a factor, we can string them together into time series. It is these time series, with their fluctuations, that represent the actual risk factors. One can use these series to observe trends in returns to a factor, for example, and adjust one's portfolio's exposure accordingly. The covariance of the returns among the time series form the factor covariance matrix. The factor return covariances are based on the last sixty monthly observations.

[3] To prevent effects from outliers, this is done by median, rather than least squares, regression

[4] For a more in-depth discussion of the logic underlying this estimation process, refer to chapter 3 of Rudd, Andrew and Henry K. Clasing, Jr., Modern Portfolio Theory: The Principles of Investment Management, Orinda, CA, Andrew Rudd, 1988.

Exponential Weighting for Factor Variance and Covariance Estimation

All factor models are based on observations of the past covariance among securities over some series of past time periods (e.g. past 60 months as in this model). The usefulness of history as a guide to the future is clearly a function of the rate of evolution of the market, its participants, and a host of other factors. The faster the rate of evolution or change in market participants, the less useful data from the distant past is as a guide to the future. This has a direct effect on the way historic data should be used for factor variance and covariance forecast calculations. Rather than view all past observations as being of equal importance, Northfield gives more recent data greater emphasis by exponentially weighting the observations.

The function e^{-nr} is used where **n** is the serial number of an observation (1st observation is the latest and n is from 1 to 60 for this model), and **r** is the decay rate. From our research, an appropriate decay rate is 0.02 for this type of US equity model.

Conditional Mean Returns for Factor Variance and Covariance Estimation

Market efficiency theory would suggest that mean alphas (returns net of market risk) to a particular factor should be close to zero over time. However, in a bubble or trending market, a particular factor may exhibit a high mean return, with low variance around the mean for a substantial period of time. This failure of our normal theoretical assumptions to hold is an additional source of uncertainty that the traditional factor return variance calculation does not capture. By revising the way that factor return variance is measured this risk can be captured.

Instead of traditional variance computation, in which the squared differences from the mean of a time series (last 60 months in this case) of factor returns are measured, we estimate variances from the average of the squared value of the factor returns over the same period. Empirically, most factor returns do have a mean close to zero, so the change will not be noticeable. However, when a factor return is consistently large and of one sign (e.g. positive returns to the internet factor during tech bubble), this procedure will inherently bias the factor variance values upwards to provide a warning of the unusual factor behavior. More on this issue can be found in:

http://www.northinfo.com/documents/65.PDF

Asset Specific Risk Adjustment Using Parkinson Volatility Estimator

The stock specific risk is initially estimated for this type of model as the time series standard deviation (60 months in this case) of the Equation (1) error term (ε_{it}). However, traditional portfolio theory assumes that these error terms are uncorrelated through time. Since empirical evidence exists that shows this assumption to be weak, we make an upward adjustment to the magnitude of the stock specific risk estimate to compensate for this effect.

In the presence of serial correlation or heteroskedasticity in returns, the Parkinson method of estimating volatility produces superior results. This method uses the observed low-to-high range of an asset's price over each time period to infer total volatility. This information is incorporated into the model as an adjustment to the asset specific risk for stocks where the Parkinson method estimates a higher total volatility than the initial risk model estimate.

The basics of the Parkinson method can be found in: Parkinson, Michael; "The Extreme Value Method for Estimating the Variance of The Rate of Return;" Journal of Business; 1980; v 53(1); 61-66.

Model as Basis for Historic Performance Attribution

For the purpose of historic performance attribution, the usage of the model is simple. Since the factor exposures of each stock in portfolio sum to the factor exposures of the portfolio, equation (1) also holds for portfolios. Once all items in equation (1) have been estimated at the stock level we can calculate the beta and factor exposures for a given portfolio and immediately observe which "bets" paid off and which did not during a particular period.

Factor Definitions

Earnings/Price	The ratio of earnings per share to the most recent month-end market price. EPS is defined as trailing twelve-month earnings as reported on the most recent quarterly report.
Book/Price	The ratio of book value per shares as reported on the most recent quarterly report to the most recent month-end market price.
Dividend Yield	The trailing twelve-month cash dividends paid per shares divided by the most recent month-end market price.
Trading Activity	The ratio of the average daily trading volume during the past year divided by shares outstanding as reported in the most recent quarterly report.
12-Month Relative Strength	The ratio of (1 + the decimal fraction price change for the security) to the average of (1 + the decimal fraction price change) for all stocks in the universe, measured over the last 12 months.
Logarithm of Market Capitalization	The logarithm (base 10) of total market value of common shares outstanding, using the most recent month end market price and the shares outstanding as reported on the most recent quarterly report.
Earnings Variability	The numerical value "one" minus the R-squared statistic for a trend line of the most recent five years of fiscal year earnings per share.
EPS Growth Rate	The annual compound percentage growth rate, consisting of a blend of 50% historic earnings per share growth rate over the past five fiscal years, 25% our expected long term earnings growth rate, and 25% the "sustainable earnings growth rate" (FY1 Return on Equity * FY1 Retention Ratio).
Revenue/Price	The ratio of trailing twelve-month revenues per share as reported on the most recent quarterly report to the most recent month-end market price.
Debt/Equity	The ratio of long-term debt outstanding to corporate net worth (total book value) as reported on the most recent quarterly report.
Price Volatility	A price volatility index calculated as the (52 week high price minus 52 week low price) divided by the (52 week high price plus the 52 week low price).

The Data File

Below is an outline of the Northfield fundamental factor model's data file. The field number refers to the column number in the data file where the coefficient for that particular variable can be found. For more information about the data file, please see the Northfield Open Optimizer documentation.

Identifier	Name	Field #	Identifier	Name	Field #
BETA	Beta	F1	ETRON	Electronics	F34
E/P	Earnings/Price	F2	CPU	Computers	F35
B/P	Book/Price	F3	SOFT	Computer Software	F36
YIELD	Dividend Yield	F4	EE	Electrical Equipment	F37
TRADE	Trading Activity	F5	MACH	Machinery	F38
RST	Relative Strength	F6	CHEMB	Chemicals Basic	F39
CAP	Market Cap	F7	CHEMS	Chemicals Specialty	F40
E VAR	Earnings Variability	F8	GOLD	Precious Metals	F41
E GR	EPS Growth Rate	F9	FE	Iron & Steel	F42
REV/P	Revenue/Price	F10	MINE	Metals & Mining	F43
DEBT/EQ	Debt/Equity	F11	PAPER	Paper	F44
PR VOL	Price Volatility	F12	MFG	General Manufacturing	F45
MBANK	Major Banks	F13	WASTE	Environmental & Waste	F46
RBANK	Regional Banks	F14	TRANS	Railroads & Shipping	F47
S&L	Savings & Loans	F15	AERO	Aerospace	F48
FINSRV	Financial Services	F16	SRVB	Services Business	F49
FINMSC	Financial Misc.	F17	SRVC	Services Consumer	F50
LIFE	Insurance Life	F18	PARTS	Auto Aftermarket	F51
INSPC	Insurance Other	F19	TOBC	Tobacco	F52
CONST	Building Construction	F20	SOAP	Soaps & Toiletries	F53
BMAT	Building Materials	F21	DRINK	Beverages	F54
FOREST	Forest Products	F22	FOODB	Foods Basic	F55
AIR	Airlines	F23	FOODP	Foods Packaged	F56
AUTO	Auto & Truck	F24	RETF	Retail Food & Drugs	F57
TRUCK	Trucking	F25	RX	Drugs	F58
CLOTH	Apparel & Textiles	F26	MEDSUP	Medical Supplies	F59
RETSG	Retail Soft Goods	F27	HOSP	Medical Services	F60
RETHG	Retail Hard Goods	F28	PHONE	Telecommunications	F61
BROAD	Broadcasting	F29	EUTIL	Electric & Water Utilities	F62
PUB	Publishing	F30	GUTIL	Gas Utilities	F63
HOTEL	Lodging & Restaurant	F31	OILBIG	Oil Integrated Majors	F64
CONS	Consumer Products	F32	PUMP	Oil Refining & Sales	F65
LEIS	Leisure	F33	WELL	Oil Extraction	F66
			OILSRV	Oil Services	F67

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