RISK CONTROL FOR ASSET MANAGERS

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CONTENTS

Tracking Error and Risk Decomposition

- Risk models are most commonly used to keep **predicted tracking error** to a benchmark within acceptable limits.

- Risk control is important, not only in protecting against **unacceptable draw downs** and **underperformance**, but because volatility in a time series of returns reduces the **compounding** of long-term wealth.

- Active managers apply skills in **stock-picking** and **factor exposure decisions** (sector/country/style etc). **Risk decomposition** of a portfolio helps keep the uncertainty of portfolio returns in the **areas of expected superior performance**.

Presentation Note: C=A-V/2. Messmore '95. Zero followed by zero results in breakeven. +20 followed by -20 results in -4.No bets that we are unaware of, that may be in areas that we have no skill. Bets that we knowingly take can be kept to a size commensurate with our level of confidence. Show this discipline to clients.

Tracking Error and Risk Decomposition

- **Exposure**, not just percentage weight. There is a great range in volatility across factors, and different bets can be neutralized or magnified, depending on factor covariance relationships. Does your risk management process differentiate between the value weights allocated to a sector/country/style, and the net economic exposure of your portfolio to that allocation's influence?
- Reconciling **top-down** analysis and **bottom-up** views: when portfolios are predominantly built by picking individual stocks, systematic risks can be taken and magnified without realizing. A well-constructed risk model guards against this.

Quality Control across Multiple Portfolios: Consistent Implied Returns

- If a portfolio is judged to be as good as it can be for the moment (in other words **optimal**), then the weight of each security position must balance expected return and expected risk at the margin. If we know the risk from our model, we have an equation that gives each holding's expected return.
- Are these **implied returns** consistent with our beliefs about **future returns** from different securities?
- Are the implied expected returns consistent across the **many portfolios** under management? If we believe security X will out perform security Y, we must believe it for all our portfolios!

Quality Control across Multiple Portfolios: Explaining Dispersion of Returns

- Outside observers may wonder if **differing returns** between **similar portfolios** is a sign of sloppy internal management. But differing client goals and preferences should produce different portfolios and therefore different returns.
- Using a **risk model** through time to predict future return differences between portfolios, establishes that observed **historic return differences arose necessarily** from client needs.

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Quality Control across Multiple Portfolios: Efficient Trading

- A large asset manager typically manages many portfolios with **heterogeneous goals** and requirements. A new security position for many portfolios may take days to be established.
- A risk model will help decide in which portfolios each purchase will have the most benefit, and should therefore be carried out with the most **urgency**. Market **Impact Costs** are a function of how quickly trades are executed, and must be weighed against the **opportunity cost** to returns, and the **increased risk** of trading slowly.

Reducing Trading Costs - Scheduled Trading, & Liquidity Risk

- Consider the trades to be done in a rebalancing as a long/short portfolio to be liquidated.
- A risk model helps determine **which trades contribute the most** to the transition of the portfolio. These are the trades that the manager will be willing to bear more cost to complete.
- Northfield can provide a **joint** measure of **factor**, **stock specific** and **liquidity risk** that accounts for the likely costs of having to trade for **larger** portfolios, or portfolios with a higher proportion of **illiquid** stocks.
- Northfield offers a **real-time trade scheduler** that fully recognizes all **portfolio** and **benchmark** holdings, and considers full **risk** and **return** characteristics along with **predicted trading cost** impact.

Building a Multifactor Risk Model: Common Structures

- The most popular representation of a factor model is:

- $R_{it} = \text{Sum}_{j=1 \text{ to } n} B_{ijt} F_{jt} + e_{it}$

- where

R_{it} = the return of **security** i during period t

B_{ijt} = the exposure of **security** i to factor j during period t

F_{jt} = the return to **factor** j during period t

e_{it} = the residual return of **security** i during period t

Note that this applies equally to a **portfolio**, because exposure values add linearly across securities.

Building a Multifactor Risk Model: Common Structures

- For a **returns** forecasting model, we hope to identify factors where the mean of the distribution of each of the factor return time series (the F_{jt} values) is statistically significantly different from zero.
- In a **risk** model, we want to select the set of factors that explains as much of the **variation** of the security as possible. There is no concern that the central tendency of the factor returns distribution be significantly non-zero.
- We look briefly at 3 different factor type specifications: **endogenous**, **exogenous**, and **statistical**.

Building a Multifactor Risk Model: **Endogenous** Factors

- This is the type most commonly used by practitioners – also known as **Fundamental** Models
- Here the key issue is that we are not making any estimates of the B_{ijt} **exposure** values. They can be **observed** exactly, such as mkt cap, div yld, P/E.
- This leaves the F_{jt} **returns to factors** to be **estimated for a particular period t**, usually by a **cross-sectional regression** analysis on the returns R_{it} of the securities in an estimation universe. The time series of estimated F_j factor returns can then be used to make a forward-looking **factor covariance matrix**.

Building a Multifactor Risk Model: **Exogenous** Factors

- In this case we directly **observe factor returns** F_{jt}. The factors could be macroeconomic, such as the change in interest rates or oil prices, or they could be market variables such as the spread in monthly returns between two stock indices. **Factor covariance can be immediately calculated.**
- We now need to estimate how the returns to these factors F_{jt} impact the return to individual stocks R_{it}. This is normally done with a time series regression of the returns for each stock, $R_{it,}$ against the returns of the chosen factors, $F_{jt.}$ This gives us the **sensitivities/exposures** B_{ij} which are now considered fixed through time.

Presentation Note: e.g. the spread between the Russell 1000 and Russell 2000 as a measure of the relative performance in the US of large capitalization and small capitalization portfolios.

Building a Multifactor Risk Model: **Statistical Factors**

- Here we make **no preconceived choice** of factors. We simply carry out a statistical analysis that will **estimate both** B_{ij} & F_j - the exposures and the factor returns.
- The best known process for doing this is **principal components analysis.** In order to solve without imposing any external views on the nature of the factors, we make the assumption that all **factor return series are orthogonal** to each other.

Building Multifactor Risk Models: Comparing Endogenous, Exogenous & Statistical

- For **endogenous** (fundamental) models, **estimation error** lies in the **factor return covariance**.
- In **exogenous** time series models, **estimation error** is in the **security exposures**.
- We should choose the model specification that maximizes the advantages, and minimizes the disadvantages, conditional on the particular market characteristics and strategy being pursued.

Building Multifactor Risk Models: Comparing Endogenous, Exogenous & Statistical – Cross Sectional Dispersion

- One consideration is the level of asset specific risks (from the $\mathbf{e}_t$ terms). **In large, transparent markets like the US, the degree of stock specific return (and hence risk) is much greater**. This usually means lower explanatory power of market movements for individual stock returns (r-squared).
- More stock specific return means more cross-sectional dispersion of returns within each time period, meaning more potential to produce superior returns by stock picking, rather than market timing. **This leads active managers to take far more concentrated "bets" in a market like the US as compared to other countries where asset specific risk is lower**. In a market where asset specific risks are low, the returns of all stocks tend to be bunched relatively closely together. There is little to be gained by taking big bets on individual stocks, so more diversified portfolios are sensible.

Building Multifactor Risk Models: Comparing Endogenous, Exogenous & Statistical

- We now have a reason to prefer one type of model. **If we are running a highly concentrated portfolio, an endogenous specification might be considered preferable**. The exposures of each stock are known exactly. The potential for errors resides in the factor covariance matrix, so the risk estimates of a diversified portfolio or a concentrated portfolio are apt to have about the same level of correctness.
- On the other hand, an exogenous specification puts the potential for errors in the exposure coefficients of the individual stocks. If our interest is in running a concentrated portfolio with only a few names, the potential for damaging errors in the exposure coefficients is substantial. However, since our exposure coefficients are normally best linear unbiased estimators, the errors in the exposure coefficients will diversify away as the portfolio is diversified. **We may prefer an exogenous specification for broadly diversified portfolios**.

Building Multifactor Risk Models: Comparing Endogenous, Exogenous & Statistical – Multi Country Coverage

- **In a global portfolio context, wide differences in accounting rules and accuracy across countries make an endogenous model less attractive**. For example, differing pension liability accounting in various countries makes comparison of price/book ratios problematic. One way around this with an endogenous model is to normalize observed exposures within each country, but this can lead to other problems: e.g. normalizing market capitalization, we get the puzzling result that the largest stocks in a small country would be considered to have extremely large capitalization in a factor representation, while in a global context these stocks should be considered small cap.
- It is also suggested that where the accuracy of accounting data is suspect, the degree of willingness to believe company specific data drives differences in r-squared across international markets.

Building Multifactor Risk Models: Comparing Endogenous, Exogenous & Statistical

- Proponents of **statistical factor models** argue that these specification issues can be avoided simply by using a blind factor specification: **let the data tell us the factors we need!** However, there are possible pitfalls. First, in order to estimate an implicit factor model we must make the assumption that the **driving factors are uncorrelated** with one another. If you asked a group of professional investors what they think are important drivers of stock behavior you would likely get answers like P/E ratios, dividend yields, growth rates, beta, sector membership and so on. None of these happen to be uncorrelated with the others.
- Secondly, blind factor models do not give us any intuition as to what the actual underlying drivers of the market may be. Few active managers are prepared to take large bets on something like "factor 6" without knowing what factor 6 is. Implicit factor exposures can be mapped onto real world factors using statistical estimation similar to returns-based style analysis, but **the reasonableness of mapping orthogonal factor loadings onto non-orthogonal real world factors is often quite limited**.

Building Multifactor Risk Models: Comparing Endogenous, Exogenous & Statistical

- The most serious problem with **blind factor models** is that they **greatly amplify sample period dependence**. Risk models are usually estimated over some past sample period. If we use a specified factor model, whether endogenous or exogenous, we can estimate the model over many past time periods, and come up with our best estimates of future factor volatilities and correlations. In an implicit factor model, there is little likelihood that factor 6 estimated over the past five years, and factor 6 estimated during, say, the five years from 1990 to 1995, would represent the same real world economic driver. As such, all of our information about future factor covariance values is solely dependent on the sample period.
- For example, consider a sample period when both growth and value stocks had similar relative returns. An implicit factor model would say that growth/value simply didn't matter and it would not be represented in the model. In a specified factor model, we could consider that the growth/value relationship did matter a lot throughout many prior sample periods. We could therefore make an informed judgment as to how much volatility to expect in growth/value factor in the future, rather than simply assume it drops out because it wasn't important in the most recent sample.

Building Multifactor Risk Models: Comparing Endogenous, Exogenous & Statistical

- Another type of sample dependency is that **blind factor models often lack the statistical power to identify factors that just impact a subset of the universe**: e.g. gold mining companies.
- Random matrix theory has been used to demonstrate that **blind factor models often incorrectly identify factors where are there is no true underlying structure of the observed returns**. Some have simulated time series of returns using uncorrelated random variables, and then tried to estimate blind factors in the data. Although by construction there should be no common factors, it was found that blind models often mistake random coincidences (noise) in the returns to be real correlations that should be represented as factors. An approximate formula is provided that discriminates between blind factors that are likely to arise from real economic drivers, and those that may just be over-fitting.

Presentation Note: Bouchard et al

Security Specific Risk, Fat-tailed Return Distributions & Serial Correlation

- Security specific risk is usually estimated for these types of models as the time series standard deviation of the residual returns, e_{it} in the factor model equation. Traditional portfolio theory assumes that these **residual returns are uncorrelated** through time, and have **constant standard deviation**.
- The frequency of **large market movements suggests this assumption is weak**, so at Northfield we compensate by ramping up our security specific risk estimate, using a method by Parkinson (1980).
- This Parkinson method uses the **low-to-high range** of an asset's price to estimate security volatility. If the method estimates a higher total volatility than the initial risk model estimate, we assume evidence of kurtosis (fat-tailed return distributions) and/or serial correlation, and **pick the higher of the 2 estimates**.

Building Multifactor Risk Models: Across Countries and across Asset Classes

- The **challenges** include:

1. Multiple portfolios with multiple benchmarks.
2. Asset classes such as convertible bonds and derivatives with complex properties.
3. Asset classes such as directly owned property, private equity or infrastructure investments, that have no visible pricing, return or risk information.

- **One approach**: model risk for each asset class separately and aggregate the risks only through the covariance matrix: the advantage is internal consistency.

Building Multifactor Risk Models: Across Countries and across Asset Classes

- There are serious **limitations**
  - Not intuitive or easily actionable - can't add exposures across many disparate models
  - With more factors than observations, covariance matrix is very likely to be unstable
  - Markets where data is sparse or unreliable have to be "synthesized" using intensive statistical approaches that are probably best recommended for patching in a few missing data points, not creating whole histories.
- **Another approach**:
  - Model risk for each locale separately with one set of exposures and factors per locale
  - Look for covariance between locales; relate the multitude of local factors from all local models through to a smaller set of global factors
  - Re-express exposures of global securities from their local factor set to the global factor set

Building Multifactor Risk Models: Across Countries and across Asset Classes

- **Lingering drawbacks**
  - Relating local factors to global factors leaves unexplained "purely local" component. Local models have their own "residual" component. Roll-up mixes the two and leaves us blind as to what are locale specific or security-specific bets.
  - Factors are not integrated across asset classes, only geographically.
  - New markets still have to be synthesized from "thin air".
- **Fully Integrated Approach - Northfield's Innovation**:

Since 2000, we have used a single parsimonious factor model for all asset classes - The Everything Everywhere Model.

With all investable assets related to the same consistent set of factors, interrelationships are easily observed and understood.

The smaller number of factors allows for stable estimation of factor relationships. Complex securities can still be modeled well with relatively few factors, by breaking the security into constituent simpler assets.

Building Multifactor Risk Models: Time Horizon

- Given the **variation** over time in equity market **volatility**, making explicit differences between short term and long term risk levels gives investors an important advantage.
- Care must be taken as to whether we are really forecasting **annual** risk (the risk expected over the upcoming year), or the **annualized** value of risk over some shorter time horizon. The transition between values of risk for different time frames must account for **serial correlation** in security returns.

Building Multifactor Risk Models: Time Horizon: Conditioning with Outside Variables

- Northfield's approach to adjusting equity risk models for **variable time horizons** is the concept of **conditioning** based on a vector of **state variables**. This allows any chosen model to adapt rapidly to changes in market conditions, but to **retain the existing factor definitions and exposures**. We are asking "how are market conditions different today compared to average during the period of history used to estimate the standard model?"
- To judge the degree of difference, an information set of state variables are defined that describe contemporaneous aspects of financial conditions, but are not used in the usual risk model. For example: the **implied volatility of options** on stock indexes (e.g. VIX) and bond futures, **yield spreads** between different credit qualities of bonds, **cross-sectional dispersion of stock returns** among different sectors and countries, and the **intra-period hi-lo** prices of individual stocks. Risk estimates from the usual model are modified according to some relationship with the degree of difference in the state variables.

Building Multifactor Risk Models: Time Horizon: Conditioning with Outside Variables

- As an example of this variable state conditioning for time horizon, if a firm's manufacturing plant were to be destroyed in a flood, it would take many observations of returns to make a new estimate of how the covariance of this firm with returns of other firms had been changed by the disaster. However, if the firm had traded options, we might immediately observe a change in the stock volatility implied in the options market.
- Recently, research on **news text flows** for **length**, **frequency**, and **sentiment** has concluded that conditioning on news content adds meaningfully to the responsiveness of risk estimates, even beyond the information from implied volatility for securities with liquidly traded options.

Presentation Note: diBartolomeo, Mitra & Mitra

Risk Control: Time Horizon & Intra-horizon Risk

- The usual interpretation of volatility and tracking error predictions is to consider the distribution of portfolio values at the **end of the horizon period**: let's assume we have a portfolio worth $1 million with an expected return of zero and a volatility of 10% per annum. We further assume that the returns are normal and are independently and identically distributed (no serial correlation and constant volatility). Then a 3 s.d. loss, equating to 30%, reduces the portfolio to $700,000 at the end of 1 year. The likelihood of this is about 1/1000.
- Since there is always some chance that the portfolio could fall below the floor of $700,000 at some point during the year, yet still end the year about $700,000, the **intra-horizon probability of given loss is greater than the probability of the given end of horizon loss.**

Risk Control: Time Horizon & Intra-horizon Risk

- How much would we have to reduce the volatility in the portfolio such that the probability of a maximum acceptable intra-horizon loss would be equal to the original probability of the same loss at the end of horizon?
- The answer (reasoning not shown) in our simple example above, with end horizon volatility 10%, we would have to reduce the end horizon volatility to 9% [10/1.11] to get roughly the same 1/1000 chance of having the portfolio value go below $700,000 at any time during the year.

Presentation Note: Nick Wade

Risk Control: Time Horizon & Intra-horizon Risk

- The other issue we must deal with when considering any **varying horizon risk** is that the **shape of the return distribution** may be different if we are measuring returns on a daily basis than if we are measuring returns on a monthly or annual basis. In general, the **shorter the observation interval** (i.e. higher frequency), the greater the tendency of the observed return distribution to have "**fat tails**", meaning that extreme moves up or down are much more frequent than would be predicted in a normal distribution.
- For intra-horizon risk, if we believe the returns for our portfolio will be fat tailed, we can upwardly adjust the scaling divisors described above to compensate. A useful approach for the size of the adjustment is from Cornish-Fisher (1937). C.F. can also be used to compensate for skewness in the return distribution, as might arise from non-linear derivatives such as options.
- When different return distributions are assumed, various papers suggest scaling divisors ranging from roughly the 1.11 above to 2.64, depending on distribution type: normal, IID, jumps, stochastic volatility, etc.

Presentation Note: Feller
Bakshi & Panayatov

Risk Control and Portfolio Construction: Custom Risk Models - Factors of User Interest

- Asset managers might wish to view returns and risks of a market through a **factor model that is particular to their needs**. Quantitative managers may be concerned about misalignment if the risk and return models are based on different factors. If the risk model and return models use the same factors, quantitative managers can more deliberately use their return forecasts to add predicted value to the portfolio.
- Similarly, fundamentally oriented managers often find factors in commercially available risk models to be unintuitive. A customized model can structure the decomposition of risk and return into sources that seem relevant to the way they view the world.
- Customization allows risk managers to **express limits in terms of user-defined categories** that may not align clearly with the available factors in commercial models.

Risk Control and Portfolio Construction: Custom Risk Models - Factors of User Interest

- If we assume that the risk model is **complete** (meaning that no relevant factors have been omitted and that residual risks are uncorrelated) then revising a factor model to make it more intuitive is quite tractable. We can simply **map any user selected factors onto the complete set of factors and then restate the relationships**. This is because some important properties follow from the assumption of completeness:

-The values of asset specific risks in a complete model are uniquely correct. If the factors account for all covariance among securities, the asset specific risks will be same for any factor covariance matrix that also accounts for all covariance among securities. Therefore **in the complete case we can leave the asset specific risks alone** when we add new factors.

-Again **with a complete set of factors, returns to any new common factor can be expressed as an exact linear combination of the original factors**, and the risk of any portfolio will remain the same, even when expressing the risk using different factors.

Risk Control and Portfolio Construction: Custom Risk Models - Factors of User Interest

- As more and more user-defined factors are added that are not linear combinations of other user factors, the unexplained portion of the original factors becomes increasingly statistically insignificant. In effect, the user could entirely replace the original model.
- The key caveat is that the properties of the user defined factor return time series be such that the linear relationship with each of the original factors can be reliably estimated by regression. The user-defined factors must be limited in number, not too correlated for the available amount of historical data, and be compliant with typical statistical estimation concerns about outliers.

Incorporating Strategy Risk into Active Management

- The applicability of **tracking error** as a measure of risk is **clear for passive** funds, but **for active managers it is more problematic**. Consider two managers: A produces returns of .25% over benchmark each and every month. B produces .25% below the same benchmark each and every month. *Both have the same tracking error: Zero!*
- **Tracking error** describes the **degree of dispersion around the mean** of the benchmark relative return, but **does not address the potential for the active mean return itself to vary and be negative**.

INCORPORATING STRATEGY RISK INTO ACTIVE MANAGEMENT

- One approach: we formulate **Active Risk** as the aggregate of tracking error around the mean return over time, and the uncertainty of the mean return itself :
- Estimate active risk as the square root of total active variance:

$$\sigma_{active} = (\sigma_{mean}{}^{2} + \sigma_{TE}{}^{2} + 2 * \sigma_{mean} * \sigma_{TE} * \rho)^{.5}$$

Where

σ_{mean} = uncertainly of the true mean relative to expectation of the mean

ρ = correlation between uncertainty and tracking error

Presentation Note: Qian & Hua

Incorporating Strategy Risk into Active Management

- As an example, we observe the 60 monthly returns ending November 30, 2009 for 1,957 US Large Cap Growth Managers.
  - Compute the monthly cross-sectional average and subtract from each observation to put observations in "peer relative excess" units
  - Calculate the cross-sectional standard deviation for each month
  - Calculate the 60 month annualized excess return
  - Calculate 60 month realized annual tracking error (standard deviation of excess returns)
- Average annualized cross-sectional dispersion is 5.76%
- Average time series tracking error is 5.70%.
- The cross-sectional correlation between the absolute value of annualized excess returns (as a proxy for dispersion of mean) and corresponding tracking errors is .21.

$$\sigma_{active} = (5.76^2 + 5.70^2 + 2 * .21 * 5.76 * 5.70)^{.5} = 8.91$$

Incorporating Strategy Risk into Active Management

- Our new measure of Active Risk represents an increase of 56% in risk as compared to tracking error alone
- This can easily be incorporated in risk budgeting and manager evaluation exercises by asset owners.
- For asset managers, portfolio optimizations can be organized as a conventional mean-variance process, subject to a constraint on the value of active risk.
- As active risk rises rapidly with expected IR, this sort of optimization procedure reduces bet sizes in an intuitive fashion, much like a Bayesian process or robust optimization
- This process has the advantage of explicitly considering the potential for realized alphas to be of the wrong sign, rather than being just overstated in magnitude

Mitigating Parameter Estimation Error for Risk & Return

- Modern Portfolio Theory involving mean-variance optimization assumes that we know with **certainty**, the expected returns, volatilities and correlations for our assets. It also assumes that the future is a **single long period**, during which these parameters never change.

- Northfield has been pointing out these limitations and various potential remedies since the early 1990's. Over the years, 3 basic methodologies have emerged: Bayesian methods, re-sampling and robust optimization. After nearly twenty years of extensive experience with all three approaches, we have concluded that all three produce quite similar results, and that **Bayesian methods** offer the most tractable process, particularly for problems with large numbers of assets (i.e. equity portfolios).

Presentation Note: Error maximization

Mitigating Parameter Estimation Error for Risk & Return - Alpha

- Northfield's Open Optimizer includes 5 features designed to help users have more **stable** and **efficient** optimization results, while reducing the required amount of data preparation.
- 3 features are for adjusting return expectations (alpha) to more realistically represent investor's beliefs:

  1) Converts user-alphas to percentile ranks, and then to Z-scores, then **scales by the user's information coefficient** and the **risk model's forecast for cross-sectional return dispersion**.

  2) The user supplies security return forecasts with confidence intervals. These are **squeezed towards each other in recognition of where securities' benchmark excess returns are highly correlated**, based on the risk model.

  3) User expected returns are **squeezed toward a prior central value** (often zero when benchmark relative). The magnitude of each asset's adjustment reflects the risk model's prediction of the asset covariances.

Presentation Note:
1) Almgren and Chriss, Grinold
2) Benchmark-relative Black Litterman
3) Jorion

Mitigating Parameter Estimation Error for Risk & Return - Risk

- With the 4th feature, the user can blend in their chosen weighting of **three alternative assumptions** to the full security covariance matrix implied from the risk model:

  1) The covariance among securities described as a single-index model (Sharpe market beta).

  2) The correlation among securities is set as constant and equal across all pair wise relationships.

  3) The covariance among securities is constant and equal across all pair wise relationships.

By **blending these alternatives with the factor model**, the **influence of outliers** on risk forecasts and optimal portfolios is **reduced**.

Presentation Note: Ledoit and Wolf

Mitigating Parameter Estimation Error for Risk & Return: Multi-Periodicity

- Portfolio Theory's assumption that the future is a **single long period with constant parameters**, can easily lead to over trading in the real world, suffering **excessive trading costs** as the manager's beliefs change:

-In our Open Optimizer, transaction costs are usually amortized over the expected holding period of a security. Our 5th new function **dynamically adjusts** the rate of transaction amortization within the portfolio construction algorithm, so as to reflect the **varying probability of actually achieving a better realization** at each iterative step in the optimization.

- This dynamic probability is based on the expected utility of the initial portfolio, the expected utility of the partially optimized portfolio, the tracking error between the two, and the expected holding period.

Northfield's US Single Country Equity Model and the Hi-Tech Bubble: S&P500 relative to US$ Cash

US SINGLE COUNTRY MODEL	January 31, 2000……………				June 30, 2005…………………		
Factor	PortExp	FactorVar	VarContr		PortExp	FactorVar	VarContr
US MARKET	1.0985	253.012	338.4316		0.865164	200.641	168.7867
INDUSTRIAL SECTOR	0.0587	413.141	20.86944		0.025622	244.321	5.190746
CONSUMER SECTOR	0.0316	243.859	8.629621		0.042219	160.501	6.860662
TECHNOLOGY&HEALTH SECTOR	0.0565	469.65	20.88155		0.023441	408.563	5.883688
INTEREST RATE SENSITIVE SECT	0.0776	241.883	19.85934		0.083857	156.678	13.28221
NON-ENERGY MINERALS	0.0041	533.906	1.193328		0.004365	629.96	0.95984
ENERGY MINERAL SECTOR	0.0373	250.872	5.257241		0.055624	298.909	7.094098
S B WORLD GOVT BOND INDEX	0.1301	17.87	1.420725		0.201777	30.5462	-5.37554
OIL PRICES IN USD	-0.0126	1550.61	-1.34194		-0.0364	1099.92	1.132755
USD FX	0.0067	47.5662	-0.00094		0.112527	63.3138	-0.76423
SIZE	-0.0861	268.934	-10.0139		-0.03594	170.222	-1.34994
VALUE/GROWTH	0.5055	12.2987	-14.6648		-0.01333	5.4667	0.208897
BLIND FACTOR 1	0.5578	12.9775	0.589042		0.506219	13.3409	-1.79021
BLIND FACTOR 2	0.208	12.8922	0.637416		0.343684	12.4321	2.805479
BLIND FACTOR 3	-0.2968	13.2985	4.999898		-0.04828	12.6632	0.050011
BLIND FACTOR 4	0.439	13.2042	-5.27403		0.454116	12.7506	-1.59446
BLIND FACTOR 5	-0.4016	13.3564	-3.24498		0.087515	12.9038	0.081725
Factor Tracking Variance			388.2287				201.4624
Stock Specific Tracking Variance			5.7285				3.2165
Total Tracking Variance			393.9572				204.679
Tracking Error			19.8484				14.3066

Northfield's US Fundamental Equity Model and the Lehman Failure: S&P500 relative to US$ Cash

US FUNDAMENTAL MODEL	September 30, 2008 1 year horizon			October 1, 2008 2 week horizon, annualized	
Factor	PortExp	FactorVar	VarContr	FactorVar	VarContr
Beta	1.012023	186.908	191.4294	1517.72	1554.435
Earnings/Price	0.2255628	4.64309	-0.53936	37.7027	-4.43452
Book/Price	-0.392107	4.20912	0.254608	34.1788	2.184906
Dividend Yield	0.1943916	6.07762	-0.30507	39.7875	-2.40408
Trading Activity	0.0811331	7.45666	-0.09939	60.5494	-0.79177
Relative Strength	0.094063	33.5588	0.677082	272.503	5.550239
Log of Market Cap	2.260423	7.16186	28.15521	58.1555	228.9793
Earnings Variability	-0.486779	3.61882	-1.14323	29.3854	-9.32815
EPS Growth Rate	-0.015222	5.01543	-0.03909	40.7261	-0.32162
Revenue/Price	-0.2342	6.19289	0.367937	50.2873	3.016
Debt/Equity	0.0647286	2.41432	0.014517	16.7199	0.0909
Price Volatility	-0.627199	13.9691	-0.48879	113.431	-3.96894
Major Banks	0.0704598	173.876	0.719186	2198.18	11.74791
Regional Banks	0.0060439	108.955	0.035406	1377.44	0.616242
Financial Services	0.0335466	48.1833	-0.00227	609.145	0.684037
Insurance Life	0.0131516	50.0179	0.045943	632.338	0.72382
Insurance Other	0.0195751	41.2517	0.079939	521.514	1.187172
50 other industries	………	……..	0.68785	………	2.551972
Factor Tracking Variance			219.8499		1790.518
Stock Specific Tracking Variance			7.4926		2.6732
Total Tracking Variance			227.3425		1793.191
Tracking Error			15.0779		42.3461

Northfield
INFORMATION SERVICES, INC.