1. I Know What To Do, Why Don't I Do It?

Nick Hall, Director, Saddlebrook Wellness Center, gave the opening address at the Spring 2006 seminar. The title of his talk might have been Decision Making Under Stress. In introducing him, Jim Farrell described him as an expert in Neuro Psychology, and referred to the fact that Hall teaches at the FBI academy.

Hall began with a childhood experience of his that gave him an important lesson in making healthy decisions and choices. It taught him to be an optimist. He referred to an optimist as not a person imagining bad experiences to be good, but an optimist in explanatory style, taking personal credit for good outcomes and blaming bad outcomes on others or other circumstances. A pessimist in explanatory style, on the other hand, attributes credit for successful outcomes to others, and accepts blame himself for unsuccessful outcomes. As an example, the successful investor takes personal credit for good results, but attributes poor results to such things as unexpected economic events. The characteristic as optimist or pessimist Hall characterized as permanent, with the optimist making healthy choices in all aspects of his or her life.

No one responds to reality just as it is. Sensory information is transferred by electrochemical transduction into an image in the cerebral cortex of the brain. That image depends on the individual's beliefs, value system, and past experience. No two people will have exactly the same beliefs, values and experience, so that no two will have identical images produced by the same event. The reality of the event is modified in our brains to leave out certain aspects and to add other aspects consistent with our beliefs.

He provided an example. He read out a series of words, all of them connected to sleep, but not including the word sleep. He asked the participants to write down as many of the words as they could recall. He then asked how many had written down the word sleep, and of course a number of participants had written the word down even though they had not heard it. But all of the words that been dictated evoked an image of sleep, and what the participants remembered was the image of sleep created in their minds.

Hall went on to describe some work he had done with cancer patients. What he called "guided imagery in cancer" meant invoking in cancer patients the image of a healing process. Once that image had been embedded in the brains of cancer patients, the result appeared in most patients to be prolonging their lives. However, in a few cases patients were so disturbed by the image reminding them of their cancer, that the development of the image had to be stopped with them.

He turned next to sources of belief. It can be important for us to know what those sources are. Indeed, even more important may be knowing just what our beliefs are and he described working with executives who had great difficulty identifying their beliefs. Consistency of beliefs with values can be quite important, and he illustrated this point with a story about a police officer for whom the conflict between beliefs and duty almost cost him his life.

He suggested three questions a person might ask him or herself about beliefs. The first is "Is this belief justified? Have things happened in my life that warrant my clinging to it?" The second question is "Is this belief serving a useful purpose? Helping me advance? Improving my relationships?" And finally a third and most important question "Does it make me feel good?" If the answer to any of the three questions is "no," then there probably is a conflict between beliefs and values and the person should try to find out why.

Another piece of advice was this: In a crisis, put a brake on your emotions and take control. Repeat three times: "I am glad I am not …" completing the statement with the description of a circumstance much worse that the present crisis.

What defines happiness? His answer was the ability to be satisfied with what you have and are.

I. Portfolio and Risk Management

2. A Rational Model of the Closed-End Fund Discount

Jonathan Berk, Professor of Finance, Haas School of Business, University of California at Berkeley had made presentation on three previous occasions at Q-Group® seminars, in Fall 1996, Fall 1998 and Fall 2003. He made available a paper by himself and Richard Stanton entitled: "A Rational Model of the Closed-End Fund Discount."

He began his presentation by referring back to the earlier one in which he had explained the flows into and out of mutual funds. In now modeling the closed-end fund discount he had arrived at a model that solved both the mutual fund flow puzzle and the closed-end fund discount puzzle. In addition, the model explains the unpredictability of fund performance, the inability of active portfolio managers as a whole to beat passive strategies while most active managers actually do display skill, and finally compensation contracts in the portfolio management industry. The focus of the current paper, however, was on the closed-end fund puzzle. The puzzle has been set out in four statements:

- Closed-end funds are issued at (or above) their NAV, more often than not start trading at a premium to NAV, and then decline.
- On average, closed-end funds trade at a discount relative to their NAV.
- The discount is subject to wide variation over time and across funds.
- Discounts disappear as the fund approaches the open end date.

The authors' objective was to derive a completely rational model that will simultaneously explain all four of these empirical regularities. He cautioned, however, that their objective was not to claim that the model explains the whole anomaly, nor that behavioral explanations have no place.

At the initial public offering of the closed-end fund investors expect managers to earn more for the fund than they charge in fees. Berk's model assumes that a few skilled managers exist, that these managers sign binding long-term contracts at fund inception, guaranteeing payment of fixed fees, and that the contracts cannot prevent managers from quitting. So investors rationally expect the average fund to fall into discount. They still get a fair return because in each period, the discount adjusts to ensure this. Since discounts are the *capitalized value* of the expected cost of entrenchment, they shrink to zero as the open end date for the fund approaches. Since discounts adjust to ensure that investors get a competitive return, they reflect the cross sectional variation in management ability, so they have wide cross sectional and time series variation, as can easily be observed.

From these assumptions it follows from the model that the funds are issued at NAV, most funds trade at a discount, the discounts disappear close to the liquidation or opening dated of the funds, and there is a wide variation in discount, both in the time series and cross-sectionally.

The model itself is:

Where
is the return on the (observable) portfolio at

the start of the period
is the expected return on the (observable) portfolio at the start of the period
and are independent normal iid r.v. with zero means and precisions and respectively.

Berk set up an example for the calibration of a closed-end fund, suggesting reasonably parameters for the model set out above, and then generated graphs of discounts (and premiums) related to manager ability, fund age, and time-to-the-opening date. Perhaps most surprising was the trajectory of the premium representing perceptions of high manager ability. Over time, the premium in such a case rises but then begins to turn down in anticipation of the opening date, when the price will equal the NAV.

In response to questions about the ability of a manager to increase its fee, Berk pointed out that an obvious way for the manager to increase its effective fee was simply to open new closed-end funds and spread the managerial talent over a larger amount of money.

To the question "What cannot be explained?", Berk's response was the post IPO 90 day return appears to be highly negative. This seems to come from the average 7% fee charged on the IPO and subsequent price support provided by the investment banks. To this explanation one participant added the observation that sales efforts by those distributing fund shares could be another explanation.

In conclusion, Berk said that with his model of what the rational paradigm predicts, we can begin to identify important departures that the behaviorists can work on.

3. Downside Risk and Its Implications for Financial Management

Robert Engle, Professor of Finance, Leonard W. Stern School of Business, New York University, who Jim Farrell observed in introducing him, is also a Nobel Laureate. He had made a presentation at the Q-Group® seminar in the Fall of 1990, and now made available a paper entitled: "The Underlying Dynamics of Credit Correlations," by himself Arthur Berd, and Artem Voronov.

Engle began with the proposition that the trade-off between risk and return is the central paradigm of finance. The risk of a portfolio is that its value will decline, hence downside risk is a natural measure of risk. Many theories and models assume symmetry and volatility based risk, and he listed some of these. But a number of measures have been proposed specifically aimed at the measurement of downside risk, measures that do not assume symmetry. Engle went a step beyond this to consider multivariate downside risk. What is the likelihood that a collection of assets will all decline? This depends partly on correlations, and for extreme moves other measures are important too. It also appears that correlations and volatilities tend to move together.

As we move to measuring joint downside risk, we ask what is the probability that one asset has an extreme down move when another has an extreme down move? We can define an indicator for default in the case of a fixed income security, and measure the correlation between the indicators for a number of such instruments. For extremes, the default correlation will be the same as the lower tail dependence.

Turning specifically to credit derivatives, Engle commented that it is well documented that the multivariate normal density under-prices joint extreme events such as defaults. Tail dependence is essential to pricing multivariate credit products like CDO tranches:

- Collateralized debt obligations are portfolios of corporate bonds.
- For a fee, an investor can be paid for the first K % of default losses in the portfolio over a period.
- The value of this derivative depends on

default correlations.

Engle next described modeling the one-period return and calculating the multi-period distribution of returns into the future. From this distribution a measure of downside risk can be computed. He proposed the GARCH model. The TARCH is like a GARCH, but gives negative returns an extra boost, reflecting empirical observations.

Moving to the sources of asymmetric volatility, a small effect is due to increased leverage. As equity prices fall, the leverage of a firm increases, so that the next shock has a greater effect on stock prices. But the more important effect has to do with risk aversion. News of a future volatility event will lead to stock sales and price declines. Subsequently, the volatility event occurs. Since events are clustered, any news event will predict higher volatility in the future. This effect is especially relevant for broad market indices, since these have systematic risk.

Evidence of skewness can be found in the high price of out-of-the-money equity put options. The implication is skewness in the risk neutral distribution, and much of this is probably due to skewness in the empirical distribution of returns. The option skew appears only post 1987.

With respect to stocks, under the standard assumptions the skewness of return is related to the skewness of the market through the correlation between stock and market. All stocks will then have skewness, but it will be less than for the market.

The probability that two stocks will both underperform some threshold can be calculated conditional on the market return. When the market return is a fat-tailed distribution then tail dependence rises. In summary, asymmetric volatility in the market factor implies:

- Skewness in multi-period market returns
- Skewness in multi-period equity returns
- Lower tail dependence in equity returns

Engle set out a number of implications of the preceding for risk management, derivative hedging, and portfolio selection. Multi-period risks may be substantially different from one period risks. The multi-period risk changes over time and can be forecast. Big market declines are more likely when volatility is high.

As each new period return is observed, derivatives can be repriced and the hedge updated. Low frequency mean variance portfolio optimization will miss the asymmetries in stock returns. High frequency rebalancing will give early warning of downside risk.

All of this implies coordination of risk management and alpha estimation.

In conclusion, Engle said:

- Asymmetric volatility and correlation models are powerful tools for analyzing downside risk.
- One period models have big implications about the long horizon returns.
- The updating of volatility and risk measures has a natural application to derivative hedging, pricing, and possibly high frequency portfolio rebalancing.

4. Harvard, Yale and the Future of Investing

Andre F. Perold, Sylvan C. Coleman Professor of Financial Management, Harvard Business School, who has spoken at five previous Q-Group® meetings, Spring 1980, 1987, 1994 and 2002, and Fall 2004. He presented a case study concerning the endowment funds of Harvard and Yale universities. He had made available a series of readings, consisting of commentary in newspapers and journals describing the management of the Harvard and Yale endowments, including performance statistics, manager compensation details, and the controversy that has arisen at Harvard University with respect to the very high compensations earned by Harvard employees managing the endowment. Perold also made available some descriptive statistics of the Yale and Harvard endowments and presented four discussion questions:

What is the best way today to invest a long-term pool of assets?

What is the best approach to making asset allocation and manager selection decisions?

How should Harvard think about internal versus external management? About performance measurement? About compensation of investment professionals?

What strategies are likely to perform best over the *next* twenty years?

He began the discussion, with a review of the statistics. Until about the year 2000, the performance of the Harvard endowment had been superior to that of the Yale endowment. Since that time Yale has edged ahead of Harvard, and in 2005 Yale's return was above Harvard's. David F. Swensen runs Yale's $15 billion endowment, and has shown extraordinary ability in choosing managers for Yale – the endowment is entirely in the hands of outside fund managers. Harvard has relied primarily on inside management, where incentive compensation has led to very substantial fees, reaching in 2003 a total of $107 million shared by six managers. (To put this in context, the fees were essentially the reward for beating benchmarks, and the total represented about 10% of the alpha generated by the managers.) Perhaps in part the result of complaints by students, janitors, alumni and others at Harvard, Jack Meyer, who had been in charge at Harvard for 15 years has resigned to form his own hedge fund, with very substantial assets and half a billion dollars of Harvard money. His successor, Mohamed El-Erian , a fixed income specialist who has spent the past six years running $28 billion in emerging-markets portfolios at bond fund giant PIMCO, has an extraordinary performance record at PIMCO.

It turns out that the asset allocation of the Harvard and Yale endowments are fairly similar, and the changes in allocation over recent years are fairly similar. In both endowments, the proportion invested in US equities has been falling over the past twenty years or so, while the proportion in foreign equities has held fairly steady, as has private equity investing, which is substantial The proportion in US bonds has been declining and investments in real assets have been rising.

In answer to a question about the sources of Harvard's superior performance, Perold responded that about 1/3 of the endowment fund's alpha was due to asset allocation and about 2/3 to selection. He guessed that the figures for Yale were probably similar.

A suggested strategy for Harvard was simply imitating the Yale strategy which had proved so successful. Perold commented that a great many endowment funds were attempting to do just that. Was it reasonable to expect that with many endowment funds trying to copy Yale, Harvard might expect to excel by doing the same? It appeared to Perold that much of the success at Yale and Harvard was due to finding good people to invest in areas largely ignored by other major institutions. Would it not make sense for Harvard to look for areas where there was little or no competition? It occurred to him that truly long horizon bets might be appropriate.

There was an extended discussion of the pros and cons of attempting truly long horizon investing. Finding qualified managers, measuring performance and setting compensation could present problems. At the same time, there was not great confidence among the participants that simply continuing with the strategies that had worked in recent years could be counted on for the long run future.

Finally, there appeared to be no consensus, and Perold closed with the comment that it will be interesting to see where Harvard goes under its new leadership.

5. Roughing it up: Including Jump Components in the Measurement, Modeling and Forecasting of Return Volatility

Francis X. Diebold, W.P. Carey Professor of Economics, School of Arts and Sciences, University of Pennsylvania, made available a paper by himself, Torben G. Andersen, Tim Bollerslev entitled: "Roughing It Up: Including Jump Components in the Measurement, Modeling and Forecasting of Return Volatility."

Diebold began by reviewing important advances in volatility measurement and modeling, pointing out that all of them were inadequate for purposes of volatility forecasting. An important improvement lay in the separation of jump and diffusive movements as components of total volatility. The answer to the question why should we care about this separation, was improved understanding of the price discovery process, and improved forecasts of realized volatility for asset pricing, asset allocation, and risk management.

He introduced his work stating "we seek to further advance the non- parametric realized volatility approach through the development of a practical non- parametric procedure for separately measuring the continuous sample path variation and the discontinuous jump part of the quadratic variation process. The approach builds directly on the new theoretical results involving so- called bi- power variation measures constructed from the summation of appropriately scaled cross-products of adjacent high frequency absolute returns. The result is to shed new light on the dynamics and comparative magnitudes of jumps across three different markets: the DM/$ foreign exchange market, the S&P 500 market index, and the 30- year US Treasury yield. The authors' new HAR- RV- VJ forecasting model incorporating jumps builds directly on a heterogeneous AR model for the realized volatility, or the HAR-RV model in which the realized volatility is parameterized as a linear function of the lagged realized volatilities over different horizons."

Diebold presented results for the three markets. The DM/$ volatilities range from December 1986 through June 1999, for a total of 3,045 daily observations. The underlying high-frequency spot quotations were kindly provided by Olsen & Associates in Zurich, Switzerland. The S&P 500 volatility measurements are based on tick- by- tick transactions prices from the Chicago Mercantile Exchange (CME) augmented with overnight prices from the GLOBEX automated trade execution system, from January 1990 through December 2002. The T- bond volatilities are similarly constructed from tick-by-tick transaction prices for the 30- year US Treasury Bond futures contract traded on the Chicago Board of Trade (CBOT), again from January 1990 through December 2005. After removing holidays and other inactive trading days, they have a total of 3,213 observations for each of the two futures markets. He showed the results in panels, displaying from December 1986 through June 1999 a plot of daily realized volatility, the daily jump component of the volatility and the statistically significant jumps.

The next step was forecasting. The authors relied on the simple-to-estimate HAR-RV class of volatility models. The HAR- RV formulation is based on a straightforward extension of the so-called heterogeneous ARCH, or HARCH class of models in which the conditional variance of the discrete sample returns is parameterized as a linear function of the lagged squared returns over the identical return horizon together with the squared returns over longer and/or shorter return horizons. The model, for daily, weekly and monthly volatilities is represented by:

the daily, weekly and monthly measures employed here afford a natural economic interpretation.

The HAR-RV model for one-day volatilities extends straightforwardly to longer horizons, . Moreover given the separate non- parametric measurements of the jump component discussed above, the corresponding time series is readily included as an additional explanatory variable, resulting in the new HAR-RV-J model,

.

The estimates for $_D$, $_W$, and $_M$ confirm the existence of highly persistent volatility dependence. Interestingly, the relative importance of the daily volatility component decreases from the daily to the weekly to the monthly regressions, whereas the monthly volatility component tends to be relatively more important for the longer- run monthly regressions. Importantly, the estimates of the jump component, $_J$, are systematically negative across all models and markets and with few exceptions, overwhelmingly significant. Thus, whereas the realized volatilities are generally highly persistent, the impact of the lagged realized volatility is significantly reduced by the jump component.

Comparing jump intensities across the three markets studied, the foreign exchange and the T-Bond markets generally exhibited the highest proportion of jumps, whereas the stock market had the lowest. Intuitively, just as the stock market crash of 1987 and the correspondingly large negative daily return on October 17 is not visible in the time series of annual equity returns, many of the jumps identified by the high-frequency based realized variation measures employed here will invariably be hidden in the coarser daily or lower frequency returns.

In concluding, the authors commented that they provide a simple and easy- to- implement practical framework for measuring "significant" jumps in financial asset prices. Applying the theory to more than a decade of high-frequency prices from the foreign exchange, equity, and fixed income markets, they find that the procedure works well empirically. The non-parametric measurements suggest that jump dynamics are much less persistent (and predictable) than continuous sample path dynamics. In addition, the high-frequency data underlying the estimates allow identification of many more jumps than do the parametric models based on daily, or coarser frequency data hitherto reported in the literature. It also appears that many of the most significant jumps are readily associated with specific macroeconomic news announcements. Finally, when separately including the continuous sample path and jump variability measures in a simple linear volatility forecasting model, they find that only the continuous part has predictive power, in turn resulting in significant gains relative to the simple realized volatility forecasting models advocated in some of the recent literature.

The ideas and empirical results presented are suggestive of several interesting extensions. First, it seems natural that jump risk may be priced differently from easier- to- hedge continuous price variability. Hence separately modeling and forecasting the continuous sample path, or integrated volatility, and jump components of the quadratic variation process, is likely to result in important improvements in derivatives and other pricing decisions.

6. Buy Side Risk Management

Kenneth J. Winston, Chief Risk Officer, Morgan Stanley Investment Management made available a paper entitled: "Buy Side Risk Management."

He began with a brief discussion of the difference in perception of risk and type of risk between sell side and buy side firms. To begin with, sell side firms put firm capital at risk to facilitate the completion of transactions and/or to make a direct profit. On the buy side, firms are hired to put client capital at risk in order to obtain a financial goal or reward for the client. A brief statement of the distinction is that the buy side's business model is to profit from successfully taking risk, while the sell side's business model is to profit from avoiding risk. Buy side risk management analyzes outcomes and probabilities and takes actions to profit from anticipated outcomes, and to limit the cost of unanticipated outcomes.

He turned next to some models for predicting volatility in the S&P 500 index. He displayed the results of applying five different forecasting methodologies to conclude that the most successful simply used the previous quarter's sample volatility to predict the next. For prediction of the MSCI EAFE volatilities from quarters of daily data the GARCH(1,1) model worked a little better than simply using the previous quarter volatility.

Absolute levels of market risk are hard to predict, but dividing predictions into an absolute level and a relative-to-markets multiplier can be helpful.

If a statistic (e.g. variance, standard deviation, VaR) is *k*-homogeneous, we can write

where *g* is the gradient. For example, combining this with the previous absolute/relative breakdown, we can write tracking variance as

where *h* is the gradient divided by benchmark variance. The dot product of *(h-2)'* provides a component- by- component breakdown of relative risk. We shall see that the gradient can be very useful as a practical tool.

Winston showed a table of factors to which a portfolio might be exposed. A column tabulated the sensitivities of the return of the portfolio to each factor. A second column tabulated a factor volatility, a third tabulated the contribution of the factor to tracking error, and the final column showed the marginal contribution to tracking error. This last item is the gradient for the factor. From the table one could compute the contribution to rate of return by changing exposure to the factor, and at the same time the contribution to tracking error. The result is that the manager can trade- off return against tracking error in making factor exposure decisions.

He raised the question whether VAR is right for the buy side. If the objective is long-term wealth maximization, then focus on VAR can lead to excessive risk aversion. But endowments and pensions that are focused on surplus-at-risk may find VAR useful.

Kurtosis had been described in an earlier presentation as an important element in downside risk. Winston has found that with longer investment horizons, kurtosis comes down.

Scenario analysis involves modeling but removes the task of assigning a probability to a particular outcome. For complex portfolios of complex instruments it may not be obvious whether the portfolio will react as desired and scenario analysis may be particularly helpful. In addition, the manager or the client may wish to shield the portfolio from adverse reaction to replays of historical disasters like October 1987.

He turned next to the subject of risk in long-short portfolios. In this case, even if the long side and the short side are lognormal, the difference is not, and is not a tractable distribution. And the difference can go negative, something that could not happen in a long-only portfolio. He presented a number of graphs, showing the terminal probability of bankruptcy, and the even more important issue the probability of reaching a stopping barrier at which point the client will simply have to liquidate its position in order to avoid bankruptcy. Important parameters were the degree of leverage, the volatilities of the short position and the long, and the estimated skill on the long and short sides. The graphs offered some useful warning signals depending on the combination of parameters. In concluding with respect to long-short portfolios, he said:

- Unmanaged long/short portfolios have large chances of unacceptable drawdowns.

- Skill can be ineffective when leverage, volatility, and correlation are not properly managed.

- Higher levels of leverage, volatility, and drawdown constraints force more frequent risk management.

7 .Putting Economics (Back) Into Quantitative Models

Vineer Bhansali, Head of Analytics, PIMCO had made available a paper entitled: "Putting Economics (Back) into Quantitative Models."

His thesis was that as we quants became more mathematically sophisticated and obtained faster processing power, the approximation and computational muscle that was a short-cut took on a life of its own, largely at the expense of the economic common sense that lies behind the purpose of investing – making superior excess risk adjusted returns. Models are too assumed to operate in a theoretically ideal environment.

He pointed out that extra expected return in fixed income typically involves the sale of explicit or implicit options. For example, duration extension yield gain implies giving an option to rebalance at forwards. Taking advantage of mortgage spreads implies giving a prepayment option. Taking advantage of a TIPS spread implies giving an inflation/deflation option. The effects of these options depend very much on economic developments. His argument was that incorporating economic principles such as demand and supply, investor behavior, preferences etc. from microeconomics and monetary policy, macro aggregates, deficits, trade balances etc. from macroeconomics can make our models more flexible and hence more robust.

He provided a number of examples to demonstrate the importance of factors that are frequently omitted in investment decision making. For example, in comparing tax exempt yields with Treasury yields, a taxable investor may conclude that the tax exempt is obviously superior, ignoring the risk that tax rates may change and there is no way to hedge that risk.

To properly put economics back into models, he proposed one, although not the only possible, framework. We begin by translating economic priors into possible economic scenarios and the realization of the factors. For example, typically but not always, low inflation and low GDP is associated with low interest rate levels and relatively flat yield curves. When pricing a credit security, the arbitrage-free price can be compared or supplemented with pricing obtained by the risk premia of these factors on the security. If under shocks of the factors a so-called arbitrage free package yields non- zero excess returns, it has to hold true that the risk-neutral price is wrong, or there are hidden factors, or there are risk- free profit opportunities. He continued: We can start by defining risk exposures in terms of specific factors. For each of these factor exposures we obtain factor risk premia. For packages that allow factor risk-premia to be hedged out, we can price using the arbitrage free approach.

Depending on our outlook of the world and the expected variation in risk premia, certain sources of risk are better than others at different times. Whenever we expect to be able to earn high risk premia in a sector, we overweight that sector.

The Taylor rule connects the short rate to the deviation of inflation and output from targets. Since the Fed appears to follow the Taylor Rule in setting the short nominal rate, this input is crucial if we want to extract the economic content embedded in the yield curve. The Taylor Rule is expressed as an economically motivated term structure model:

r^* = Real funds rate
π^* = Target inflation rate – PCE deflator
u^* = Target unemployment rate – proxy for output gap

The Taylor Rule is the building block for the yield curve. The short rate is set by the Fed and transmitted across the yield curve by the no-arb condition. Yields are expectations of an exponential in short rates.

Given the economic variables in this model we can test to see the impact of changes in those variables, and Bhansali showed the effects in past years of changes in parameters included in the rule. We know from experience that Treasury yield curve fluctuations can be described by at most three factors and in most circumstances by two factors. We also know that risk- free fixed income securities are predominantly determined by inflation and inflation expectations, Fed behavior and risk premium. So a simple economically well-specified model is better suited to fit the market than a very general model that has little to do with the real world. The model is efficient enough to stress test with. At PIMCO he reported an extension where credit risk, prepayment risk and tax risk are introduced into the model explicitly from the start with stochastic intensities correlated to macro factors.

He closed his presentation with a quotation from Myron Scholes:

> "We make models to abstract reality. But there is a meta-model beyond the model that assures us that the model will eventually fail. Models fail because they fail to incorporate the inter-relationship that exists in the real-world."
>
> Myron Scholes, NY, Fall 2005.

8. Liquidity Risk in the Corporate Bond Markets

George Chacko, Associate Professor of Finance, Harvard Business School made available a paper entitled: "Liquidity Risk in the Corporate Bond Markets."

Chacko started with the proposition that any investor holding a security or a portfolio of securities or considering purchasing a security is exposed to liquidity risks. (As Chacko points out, it is *illiquidity* that presents the risk.) The difficulty in testing the effects of illiquidity is that trading volume is very low for most bonds, and virtually non-existent for truly illiquid bonds. To deal with this problem the author constructed a new liquidity measure that assesses the *accessibility* of a bond rather than its trading volume. If a bond is readily accessible, meaning that a dealer can call up one of a number of buy-side clients and obtain the bond easily, the bond can be thought of as liquid even through it may not actually trade much. The procedure was to construct a statistic known as latent liquidity, which measures the accessibility of a bond to dealers based on the aggregate trading characteristics of investors holding the bonds.

The source of data was one of the world's largest custodians. The custodian knows not only the transactions level information but also portfolio holdings. For any bond issue, Chacko was able to aggregate all of the funds holding that issue to calculate the weighted average turnover value for that issue. That value then became the latent liquidity measure for that bond.

Next was answering the question whether liquidity risk is priced or not. The procedure was to sort the universe of bonds into categories by duration
risk, credit risk, and liquidity risk. From loadings on these factors it was possible to form long-short portfolios to construct a time series of the duration, credit and liquidity factors. With these factors it was then possible to conduct some simple regressions to determine whether the

liquidity factor is priced.

To construct the liquidity factor, the universe of corporate bonds over the last 10-years (approximately 25,000 bonds) was sorted into twenty-seven buckets on a monthly basis. For each month, the sort is done first by placing each bond issue existing at that point in time into a high, medium or low duration bucket. The sort is done so that each bucket contains the same number of bond issues. Therefore the duration cutoff to go from one bucket to another varies through time.

Similarly three credit buckets and three liquidity buckets were created. Each duration bucket was sorted into one of three equal-weight credit buckets to give a total of nine equal weight buckets. Finally, each of these nine buckets was sorted into one of three equal-weight liquidity buckets so the process yielded a total of twenty-seven buckets each with unique duration, credit and liquidity risk characteristics.

From the twenty- seven buckets three factor portfolios were formed – a duration, a credit, and a liquidity factor portfolio. To form the duration factor portfolio, we take a long position in the high duration portfolio and a short position in the low duration portfolio. Similarly, to form the credit factor portfolio we take a long position in the low credit and a short position in the high credit portfolio. Finally, to form the liquidity factor portfolio we take a long position in the low latent liquidity portfolio and a short position in the high latent liquidity portfolio.

The time series of each of these portfolio returns represents the returns from the duration, credit and liquidity risk factors.

Factor regressions were conducted with each security regressed against the three factors to obtain duration, credit and liquidity betas for the security. The bonds are then sorted by their respective betas. Next, five equal- weight liquidity portfolios are formed, corresponding to five levels of beta, from high to low. Each of the five liquidity portfolios is split into three credit portfolios, high credit, medium credit and low credit. Next, each of the fifteen buckets was split into three more portfolios based on duration. A regression was run of each of the forty-five portfolios against the factors. It was clear that as the liquidity level of the portfolio decreases, the liquidity factor coefficient increases along with its t-statistic. The liquidity factor is important in the pricing of corporate bonds.

The next question was whether the risk being priced was diversifiable. The beta-sorted portfolios were run through several asset pricing models against common measures of systematic risk factors. A table of alphas from running each of the five liquidity portfolios against the bond market indicated that liquidity risk is indeed priced. Nor does the alpha disappear when each of the liquidity portfolios is regressed against the duration and credit factors.

Finally, the liquidity risk factor was tested against the returns of US Treasury bonds. Empirical work in US Treasuries has indicated that there are three important factors, level, slope and curvature factors in the yield curve. Adding the liquidity factor and constructing a four-factor term structure model showed that the contribution of liquidity (or perhaps more properly illiquidity) made a significant contribution to Treasury bond yields.

Chacko went on the show that a practical implication can be found in convertible arbitrage, that is going long a convertible bond and shorting the equity of the firm issuing the bond. Regressing convertible arbitrage returns against various explanatory variables, it turned out that the liquidity factor appeared to be very important in explaining the performance of the arbitrage. In fact the apparent outperformance of convertible arbitrage may simply be due to leaving out an important risk factor in performance evaluation. The returns are fair compensation for the risk being taken.

In conclusion Chacko said that in addition to finding very strong evidence that the liquidity risk factor is an important determinant of bond returns and is priced, the out-of-sample test on US Treasury bonds showed that the factor can be important in explaining returns in a number of asset classes, and can therefore be thought of as a universal risk factor.

9. Returns to Portfolios of Movies

Andrew Rudd, Managing Partner, and Mark Ferrari, Director of Research, Procinea Management LLC, presented a series of slides describing the movie industry and the development of a model for selecting movie investments. Rudd has made or participated in a dozen presentations at Q-Group® seminars, the most recent in Spring 2000.

Rudd began the presentation with a general discussion of the movie industry as an alternative asset class for investments. It has been the beneficiary of significant co-financing over the years but the total return has not proved exciting. Procinea has undertaken an active quantitative strategy to deliver attractive returns as part of a broader initiative to analyze the investment potential of artistic and intellectual property.

A major issue has been to define an appropriate contract to align interests between investors and studios. Unsuccessful attempts by previous investors have led to skepticism.

A second major issue is identifying an investment strategy. Rudd's focus was on movies distributed by the major studios and their subsidiaries, movies that are contracted for world-wide distribution. Behavioral problems are significant. The creative people in the movie business have agendas that appear to conflict with those of business managers. Their motivations can be difficult to reconcile with financial success.

Turning to a breakdown of the roughly $100 billion retail revenue for the movie industry world-wide, Rudd pointed out the perhaps surprising observation that US box office revenue has actually been rising over the past fifteen years. The same is true of the slightly larger international box office revenue. US home video revenue is larger and rising faster as is international home video. Overall, revenue has risen from about $35 billion to $100 billion over the fifteen year period.

Major studios finance 100-125 titles per year. The average production and distribution cost of each title exceeds $100 million, creating an annual funding need of $10-12 billion. The studios do not have the capital needed and have a long history of using co-financing partners. Procinea estimates a funding gap of $5 billion or more per year, one that is liable to increase as the number of films and costs per film rise.

An average production cost of $60-70 million is incurred over twelve to eighteen months. Prints and advertising (P&A) can be as much or more than production costs when foreign marketing is included. Revenue is earned relatively quickly after release, with 60% in the first year and almost 90% by the end of the second year. Procinea focuses on "first cycle" revenues.

An interesting question is when to invest in a movie. The choice is essentially between the "greenlight" time, when production is authorized, and the later date of the film release. Waiting until the release date risks adverse selection by the movie producer.

The Procinea policy is to invest at greenlight.

From 1997 to 2004, 1627 movies were released in the US or Canada, with a minimum production cost of $2 million. About 836 were eligible for investment, and 588 constituted a target universe for Procinea. All were financed or co-financed and distributed by a major studio. It is important that 60% of all movies do not cover their costs. Of the target universe, 57% lost money, and while the mean return on investment was 10.7%, the median was -10.2%. These statistics were considerably better than those for the broad universe of movies.

Rudd discussed a number of model issues. Revenue is clearly non-linear in movie attributes. Interactions between the attributes are likely to be important. Many interesting movie attributes are not publicly available, including actor compensation. It is not an optimistic sign that the studios themselves have difficulty predicting success. There is a significant academic literature on the subject of movies and movie investing and the conclusions are generally negative for investors.

Mark Ferrari took over the presentation to describe the development of a revenue model. He relies on standard industry data sources, augmented with extracts from on- line entertainment media, media research reports, etc. He himself defines and collects movie attributes not provided by vendor and industry sources. An example is the order in which movie casts are billed. His database includes up to 70 data points per movie, for more than 7,800 films.

Production cost is important. A regression line, as well as clustering of data points, indicated that log revenue rises more or less linearly with log production cost. There are, however, many significant outliers. The data covered 1995-2004.

Procinea's proprietary hit ratio D quantifies the past financial performance of a director. The correlation of production cost C and hit ratio is 0.34. Both factors and their interaction are significant predictors of revenue R_i of movie i according to an ordinary least squared regression. The model takes the form:

Some conclusions drawn from the model estimation are that a better director increases log revenue for any budget. A little skill really helps a small project. A little cash really helps a struggling director. Excellent directors cannot outperform if cash-constrained.

Revenue depends on the season of the film release and the rating. Both effects are significant at the 95% level. It turns out that important predictive factors are the primary genre from a Nielsen classification. It also appears that quality is rewarded, based on regressions of revenue and rating scores between 0-100 obtained from metacritic.com, which aggregates movie reviews. Story elements also influence revenue, in this case independently of their correlation with genre.

Finally, the revenue forecasting factors are production cost, talent (director, actor, writer, producer, …), studio, rating, season of release, genre, story elements, demographics, run time and interactions (teams repeat, stars specialized by genre, …). A decision rule for each movie is that:

- Given attributes at greenlight, the model predicts total revenue.
- Total revenue is divided among channels according to historical fractions.
- Channel revenue is scheduled according to historical time envelopes.
- Value is estimated as the present value of these cash flows at a fixed required rate.
- Project is accepted if value exceeds fully loaded production cost, including a cost-dependent estimate of P&A.

141 movies (24% of target universe) were selected from 1997 – 2004.

10. Participant Reaction and the Performance of Funds Offered by 401(k) Plans

Edwin Elton and Martin J. Gruber, Nomura Professors of Finance, Leonard N. Stern School of Business, New York University have appeared at eleven Q-Group® seminars, the most recent being that in the Spring of 2000. They made available a paper by themselves and Christopher R. Blake, entitled: Participant Reaction and the Performance of Funds Offered by 401(k) Plans.

There are many interesting topics related to private and public pensions. The authors had chosen two: Do companies offer participants adequate choices and do companies offer participants the "right" choices? Their presentation also dealt with the responses of individuals to those choices. There has been a large amount of research on participant behavior, but almost none on the choices given to the participants.

The data selected came from Moody's survey of pension plans, for 401(k) plans that offer only mutual funds with or without money market accounts, GICs, stable value funds and company stock. 417 of these funds used mutual funds with at least 5 years of data.

The major source of data was the 11-K filings for 401(k) plans with the Securities and Exchange Commission. These filings are required every year for all 401(k) plans that offer company stock as an investment choice. From the plans filed in 1994 through 1999, the authors excluded those where the participant flows could not be identified, plans that offered non-public stock or bond funds, and plans that had less than 4 years of contiguous data or where the plan was a duplicate of another plan offered by the same company. The final sample included 43 plans. From the 11-K filings it was possible to determine the investment choices that were offered by each plan in the sample, the amount invested by participants in each choice as of each 11-K reporting date, the allocation of new money each year, and the reallocations across existing accounts.

The first question addressed was how well the funds selected by plan administrators perform compared to funds they could have selected. The actions of plan administrators are vitally important to plan participants, since for over 60% of the plan participants the 401(k) plan represents their sole financial asset outside of a bank account. And for many plan participants that have other investments, the 401(k) represents the majority of their financial wealth. Over the 289 plan years examined, there were 215 additions and 45 deletions of funds held. It turns out that on average plan administrators select funds that underperform passive portfolios with the same risk but outperform randomly selected funds from the same category. Much of the outperformance is due to lower expense ratios. The performance measure was a differential alpha. This is the alpha for a mutual fund minus the average alpha for funds of the same general size from the same category.

Administrators add funds that have performed well in the past and drop funds that have performed poorly, and they add categories that have performed well in the past. However after the plans make a change the preponderance of evidence is that deleted funds did better than added funds, although the differences are not statistically significant. There seem to be differences in skill in selecting funds by plan administrators, but the principal predictive power is with the poorer performing plans. Bad performance predicts bad performance.

Turning to participant behavior, an interesting question was the importance of contributions and transfers in determining changes in investment weights. The authors compared the differential alphas for four weighting strategies. These were the actual participant weights, the 1/N method (equal investment in each investment choice), 1/N using the top half of past performance, and 1/N in each category. Participant weights were outperformed by each of the other strategies. But with one exception, the differences in the alphas were not significant. Theory would suggest the benefits of using contributions and transfers to restore the weights that had been altered by investment performance. It turned out, however, that the changes in weights from contributions and transfers were generally in the same direction as the change brought about by investment returns. Furthermore, contributions and transfers were equally important with investment returns in changing investment weights.

Finally, the importance of company contributions in the form of company stock was examined. In all plans, participants in the aggregate had a median investment in company stock larger than they did in other accounts. If the company's contribution was in the form of company stock, the participants held in company stock a median of 2.75 times the average amount invested in all funds, and participants still added additional money to the stock account.

Overall, there is no significant evidence to indicate participant allocations are superior or inferior to equal investment allocations. So the principal factor affecting the performance of participant 401(k) portfolios is the set of investment choices offered.

11. Persistence, Predictability, and Portfolio Planning

Michael Brennan, Emeritus Professor Anderson School of Management, UCLA made available a paper by himself and Yihong Xia, entitled: "Persistence, Predictability and Portfolio Planning." Brennan spoke at the Fall, 1981 Seminar of the Q-Group.

In introducing the topic of dynamic portfolio optimization, the authors observe that the debate about excess stock price volatility, the evidence of mean reversion in stock prices, and of the predictive power of instruments such as the dividend yield, the book-to-market ratio, the term spread and the short term interest rate, have revived interest in dynamic portfolio theory in recent years. This interest has been further stimulated by the behavior of stock prices in the late 1990's, which drew attention to the implications of valuation ratios such as the market dividend yield and the book to market ratio for expected future returns of equity securities, and therefore portfolio strategies. Failure to take account of time variation in expected returns may carry significant costs.

In concluding, their paper the authors summarize: we have shown that time variation in expected returns that implies both large variation in stock market valuation ratios and substantial gains to long term dynamic investment strategies is likely to be hard to detect by standard statistical methods. As a result, weak statistical evidence for return predictability does not in itself imply that return predictability is economically insignificant. We suggest that it is likely to be more productive to estimate the expected long run rate of return by comparing the current level of stock prices with forecasts of expected future dividends in the dividend discount model (DDM) paradigm. This forward-looking approach has the advantage that it does not rely on hard-to-estimate regression coefficients from past data. The disadvantage is that the rate of return that emerges from the dividend discount rate model is a *long run* expected rate of return. In order to use the DDM expected rate of return estimate in a dynamic portfolio planning, we show how the instantaneous expected rates of return can be estimated from the DDM long run expected rate of return.

For the standard Dividend Discount Model (DDM) the authors used growth estimates from various sources, including IBES. The DDM gave long-run expected returns k_t. For estimating the series of shorter run rates, the authors employed two methods to convert the DDM results into estimates of $_t$, the instantaneous expected rate of return. The first assumed that the dividend growth rate is a known constant and the second assumed that the growth rate followed an Ornstein-Uhlenbeck process. Both methods assumed that the instantaneous rate of return follows the O-U process described by:

(1)

(2) .

Where *dzP* and *dz* are correlated standard Brownian motion with the correlation *P.* In this formulation *t* is to be thought of as a perfect *signal* of the drift of the asset price process, *+t*.

However for the most part they assumed that = 0, and = 1. Then can be interpreted as the drift of the stock price. is the long run mean of *,* and is the speed of mean reversion. For the development of this particular model, the unconditional distribution of was fixed by = 9%, with a standard deviation of 4%. So a single sigma interval for was 5% - 14%. This is consistent with a 14% annual stock return volatility. They also assumed a risk free rate constant at 3%, implying a 6% equity premium. The authors developed nine scenarios from the combination of = 0.02, 0.10, 0.5, and = *corr* (dz_p, dz) = 0.0, - 0.5, - 0.9. The nine scenarios make up the simulation model.

The time series of $_t$ can be estimated from the time series of k_t by an iterative process using a set of parameters, starting with assumed values. They calculated , and then from the time series of they estimated the parameters and a new series of was calculated and the process was continued until convergence was reached. If the dividend growth rate expectations are stochastic, the instantaneous dividend growth rate is assumed to follow an O- U process and two steps are required to derive from k_t.

Quarterly data for real and for nominal dividends and the price- dividend ratio for the S&P 500 Index were used for the sample period 1950 first quarter to 2002 second quarter. The real and nominal long- run expected rates of return were determined at each date. Four series were actually estimated, using different sources for the long- run growth rates. Brennan discussed the differences in results among the methods, particularly the differences between forecasts of real and nominal rates of return.

To test the return predictability of the model, the authors regressed actual quarterly rates of return on the S&P 500 Index on the series of estimated . The results indicated weak statistical evidence of predictive power of the series at a quarterly horizon.

The next step was to simulate the optimal and unconditional asset allocation policies using each of the four series forecasts for . A graph showed that the investor who had followed either of two of the strategies would have vastly outperformed one following an unconditional strategy. Two of the strategies showed smaller superiority.

In conclusion, the authors said while we should be careful from inferring too much from these historical simulations which represent only a single path of stock prices for a single level of risk aversion, it is encouraging that the optimal dynamic strategies tend to outperform naïve unconditional strategies even when they are based on real time data.