Project Proposals for MS&E 444

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1 Portfolio Construction using Prospect Theory

Single asset:

-Maximize expected long run profit based on log-utility function (Kelly criterion) using student-t distribution

$$\left\langle \log(1+hx) \right\rangle_{P(x|\mu,\sigma)}$$

-Prospect theory: Investor risk aversion enhanced

$$\left\langle \log(1+hx) \right\rangle_{P(x|\mu,\sigma)^a}$$

-Time-asymmetric risk aversion:

From money-manger's point of view, get paid m%/year payed continuously plus p% change in wealth paid out annually (m=1, p =20)

-Connection to Project 2 B?

Data: One of our portfolio returns, un-levered

Multi-asset:

-How to define joint distribution function, if we assume that each single asset follows a student-t, with high negative co-kurtosis. Copulas? Which one?

-Prospect theory: Enhance investor risk aversion

Data: Index data for SPX, FTSE, STOXX 50, TPX

Monte-Carlo simulations: Create your own Student-t, correlated data

2 Optimal trading rules

The problem of finding an optimal trading rule for a mean-reverting process
has been explored for example for the Ohrenstein-Uhlenbeck process for
No transaction costs or budget constraint (M. Boguslavsky, E. Boguslavskaya, 2004)

We would like to extend this to:

Case A:

-Transaction costs and finite budget (eg $1 Million) with margin requirement
(eg $100000 per trade)

- Process with more memory that O-U process

Case B:

-To find a trading rule for a real strategy with a kink in the utility function

Data: We will provide a time-series of expected returns for a proprietary strategy

2 B Real strategy with kink in utility function

Daily expected return (ER)

Shape = Student-t with 5 df
Scale = daily volatility = 1%
ER distributed over (0,50bp) approximately

Problem: How many units to trade each day

Each year:
m% annual management fee (accrued daily)
p% performance fee on annual return, accrued on December 31

- Hold back of the prior year's performance fee, B>=0, against which "negative performance fee" can be offset (i.e. Payment kink point for annual return may be <=0)

- Or may have a hurdle rate, equivalent to B>0

Manager and investor:

- Different utility functions close to kink
- For positive returns U(W) = (W^g-1)/g, perhaps different values of g

-Using Dynamic Programming we can solve for the optimal trading rule.

Questions:

What conflicts of interest arise in the neighborhood of the kink?

Would the manager ever want to take risk off that table? When?

How sensitive is the rule to the assumed shape of returns?

Can we take into account life after Dec 31? E.g. If returns are terrible, the manager might be fired. If returns are worse than the holdback, the manager will have to recover to a high watermark in following year to get paid.

3 Hedge Fund Replication

Asset-based Style Factors for Hedge Funds, D. Hseih and W.Fung, Financial Analyst Journal, 58 (2002), 16-27

Monthly hedge fund returns are projected onto a set of factors.

Things to look at:
Factor exposures, market timing and tracking of hedge fund performance.

-Fundamental factors
-Henriksson-Merton market timing test

Data:

- EvA daily returns for several different strategies
- Upon request large hedge fund data base, monthly returns

4 Detecting insider trading

- Insider trading is quite common and occurs in stock and options markets (large trades or spikes in volume ahead of an important event, see sources on website)
- What are the salient statistical patterns?
- Can we accurately predict a future event based on suspicious trading activity?
- If so, how can we profit from this ability? Can we generate excess returns persistently? Design trading strategies and back test them

5 Trend following and market sentiment detection

Technical analysis tools often used, such as moving averages etc.
Can we instead use other techniques from signal processing?

Example would be: Machine Learning
Hidden Markov models
Wavelets

In particular can we detect when a particular market behavior or model brakes down and a new behavior starts?

Data:

-Financial time series of stock prices and volatilities

6 Extreme correlation and catastrophic events

Is there any way of predicting extreme correlations in stock moves, or catastrophic events?

For example: August 2007, stock specific (Amaranth), Black Monday, 1929, bubbles

To look at: Are there any changes in the distribution or the dynamics that can give us clues?

Are there any other variables that can help predict, such as volatility or dispersion?

Some ideas:

- Omega statistics
- Joint Distribution - look at implied copula parameters
- Principal Components Analysis: Look at portfolios corresponding to first few PCs. How does the correlation or other statistics/dynamics behave over time?
- If we define the process as absolute returns larger than a threshold, can we model with self-exciting stochastic process?
- Omori law for volatility?

Data: Price time series of stocks

7 Multi-factor model for implied volatility changes

Data:

- q-alpha-sigma implied volatility - captures tails and skew (EvA proprietary, available for about 100 stocks over 10 years)

- At-the-money Black Scholes implied volatility (OptionMetrics Database, available for all optionable stocks)

Treat volatility changes as price changes. The problem becomes similar to a standard principal components model for stocks to create a risk model for option volatilities. Co-variances will be important. Term-structure also.

A comparison between q-alpha-sigma model and the Black-Scholes model could shed light on tail and skew risk. This would be very interesting.

8 A model of volatility

Last year one project was to model volatility by a self exciting process.

This year, we would like to continue this project and in particular see if such a model can reproduce the stylized facts that are observed in real data, such as:

-fat-tailed distribution of returns

-close to log-normal distribution of volatility increments

-power law decay (auto-correlation) of volatility

-time asymmetry of volatility correlations between past and future

-Omori law for volatility

-Multi-fractal scaling of higher moments

Data: Financial time-series of stock prices