

# Practical weight-constrained conditioned portfolio optimisation using risk aversion indicator signals

Marc Boissaux    Jang Schiltz

Luxembourg School of Finance  
Faculty of Law, Economics and Finance  
University of Luxembourg

Workshop on Investment Funds  
Luxembourg, March 2011

# Outline

- 1 Context
  - Portfolio optimisation with conditioning information

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- 2 Empirical study
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# Problem context

- Discrete-time optimisation
- Minimise portfolio variance for a given expected portfolio mean
- Postulate that there exists some relationship  $\mu(s)$  between a signal  $s$  and each asset return  $r$  observed at the end of the investment interval:

$$r_t = \mu(s_{t-1}) + \epsilon_t,$$

with  $E[\epsilon_t | s_{t-1}] = 0$ .

- How do we optimally use this information in an otherwise classical (unconditional mean / unconditional variance) portfolio optimisation process?

# Problem history

- Hansen and Richard (1983): functional analysis argument suggesting that unconditional moments should enter the optimisation even when conditioning information is known
- Ferson and Siegel (2001): closed-form solution of unconstrained mean-variance problem using unconditional moments
- Chiang (2008): closed-form solutions to the benchmark tracking variant of the Ferson-Siegel problem
- Basu et al. (2006), Luo et al. (2008): empirical studies covering conditioned optima of portfolios of trading strategies
- Boissaux and Schiltz (2010): optimal control formulation of problem that allows for generic numerical solutions

# Possible signals

Taken from a continuous scale ranging from purely macroeconomic indices to investor sentiment indicators. Indicators taking into account investor attitude may be based on some model or calculated in an ad-hoc fashion. Examples include

- short-term treasury bill rates (Fama and Schwert 1977);
- CBOE Market Volatility Index (VIX) (Whaley 1993) or its European equivalents (VDAX etc.);
- risk aversion indices using averaging and normalisation (UBS Investor Sentiment Index 2003) or PCA reduction (Coudert and Gex 2007) of several macroeconomic indicators;

## Possible signals (2)

- global risk aversion indices (GRAI) (Kumar and Persaud 2004) based on a measure of rank correlation between current returns and previous risks;
- option-based risk aversion indices (Tarashev et al. 2003);
- sentiment indicators directly obtained from surveys (e.g. University of Michigan Consumer Sentiment Index)



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# Aim

- Carry out backtests executing constrained-weight conditioned optimisation strategies with different settings

# Data set

- 11 years of daily data, from January 1999 to February 2010 (2891 samples)
- Risky assets: 10 different EUR-based funds commercialised in Luxembourg chosen across asset categories (equity, fixed income) and across Morningstar style criteria
- Risk-free proxy: EURIBOR with 1 week tenor
- Signals: VDAX, volatility of bond index, PCA-based indices built using both 2 and 4 factors and estimation window sizes of 50, 100 and 200 points, Kumar and Persaud currency-based GRAI obtained using 1 month and 3 month forward rates

# Individual backtest

- Rebalance Markowitz-optimal portfolio alongside conditioned optimal portfolio, both with and without the availability of a risk-free proxy asset, over the 11-year period
- Assume lagged relationship  $\mu(s)$  between signal and return can be represented by a linear regression
- Use kernel density estimates for signal densities
- Estimate the above using a given rolling window size (15 to 120 points)
- Use direct collocation method for numerical problem solutions

## Individual backtest(2)

- Obtain efficient frontier for every date and choose portfolio based on quadratic utility functions with risk aversion coefficients between 0 and 10
- Compare Sharpe ratios (ex ante), additive observed returns (ex post), observed standard deviations (ex post), maximum drawdowns / drawdown durations (MD/MDD) of both strategies

# Set of backtests

- Decide on one baseline case - VDAX index, 60 point estimation window, weights constrained to allow for long investments only
- Vary these parameters to check both for robustness of strategy results and whether results can be further improved while staying with a linear regression model for the relationship between signal and returns

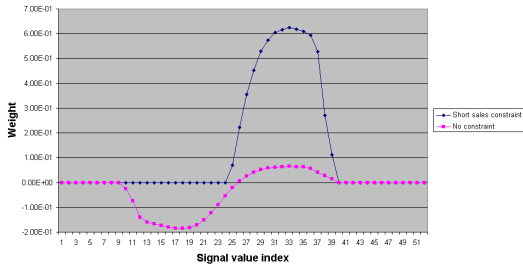
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## Results

# Typical optimal weight functionals with and without weights constraints

Example optimal weight as a signal functional in constrained, unconstrained cases

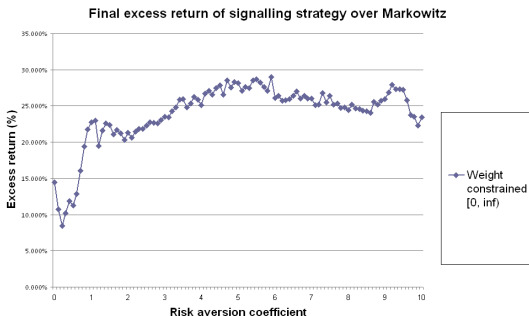


- Constrained optimal weights are not simply a truncated version of the unconstrained optimal (Ferson-Siegel) weights
- Note reduction of leverage for extreme signal values



## Results

# Base case (with risk free asset): ex post observed relative excess additive returns

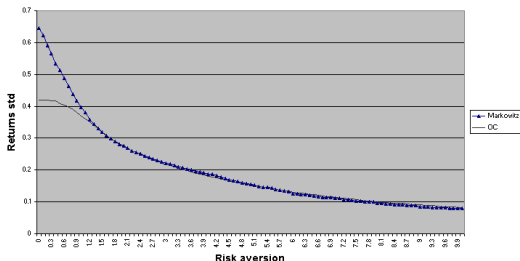


- (Ex ante) average Sharpe ratios: Markowitz - 0.325, using signal - 0.466 (using business daily returns and volatilities)
- General observation: higher risk for Markowitz at low levels of risk aversion, otherwise stable outperformance by conditioned strategies

## Results

# Base case (with risk free asset): ex post observed standard deviation ratios

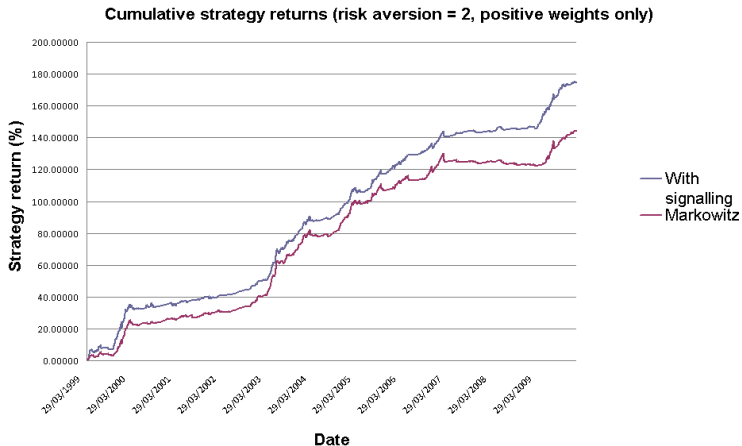
Ex post returns std for different risk aversion coefficients, VDAX, 60D window



- General observation: Conditioned strategy ex post risk is significantly lower for low levels of risk aversion and slightly higher over the remainder of the range
- Plausible given the typical shape of the conditioned solution

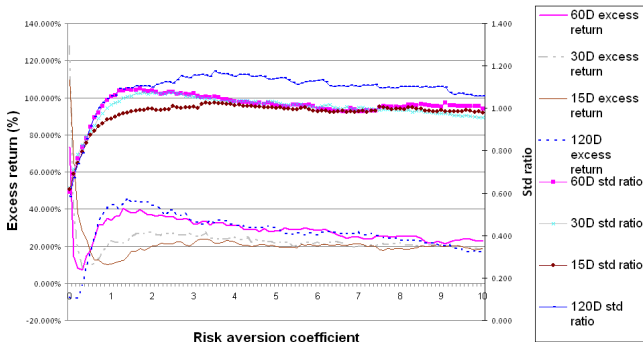
## Results

# Base case (with risk free asset): Time path of additive strategy returns for $\lambda = 2$



# Ex post results for different estimation window sizes

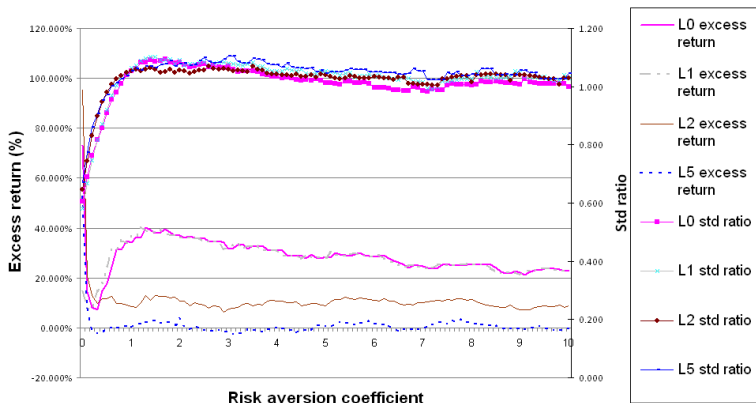
Observed excess returns and std ratios for risky asset only case, different estimation window sizes (conditioned wrt Markowitz)



- Excess returns (and standard deviations) larger as window sizes increase
- Tradeoff between statistical quality of estimates and impact of nonstationarity

# Ex post results for different signal lags

Observed excess returns and std ratios for risky asset only case, different signal lags (conditioned wrt Markowitz)

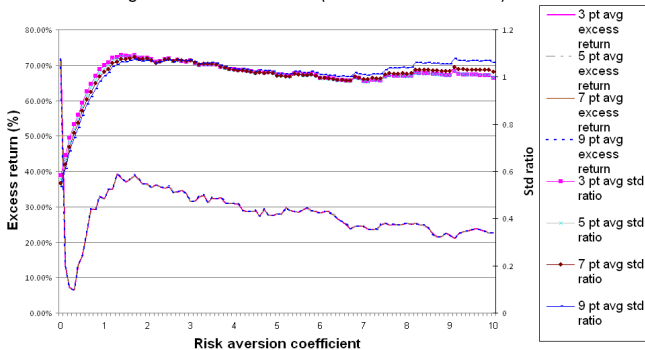


- Signal adds value for at least two additional lags

## Results

# Ex post results for weight averages over different numbers of signal points

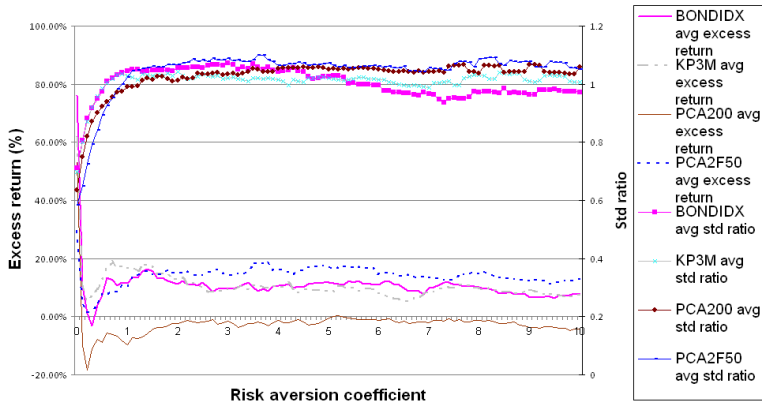
Observed excess returns and std ratios for risky asset only case, averaging weights over different intervals (conditioned wrt Markowitz)



- Negligible changes in excess returns, slight changes in standard deviations: little risk attached to signal observations

# Ex post results for different signals

Observed excess returns and std ratios for risky asset only case, using different conditioning signals (conditioned wrt Markowitz)



- Best results seen for baseline VDAX signal, averaging seems to detract from signal power

# Summary

- Backtesting using a number of different settings shows robust outperformance of the Markowitz strategy given a useful signal is exploited
- In any case, the present strategy shares the characteristics of the Markowitz approach and, as such, the consistently observed improvements reported make it interesting to practitioners investing within the mean-variance framework
- The gap between ex ante and (less good) ex post results as well as the results for lagged signals suggest that use of a signal-return relationship model that captures both autocorrelation and heteroscedasticity is likely to lead to further improvements