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An Optimal Control Solution to the Constrained Weight Portfolio Optimisation Problem with Conditioning Information

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6th Conference in Actuarial Science and Finance Samos, June 2010

Outline



Portfolio optimisation with conditioning information



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Outline



Portfolio optimisation with conditioning information



- Theoretical results
- Algorithm testing

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Portfolio optimisation with conditioning information

Outline



• Portfolio optimisation with conditioning information

Main contributions
Theoretical results
Algorithm testing

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Portfolio optimisation with conditioning information

Problem context

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

 $r = \mu(s) + \epsilon$, with $E[\epsilon|s] = 0$.

• How do we optimally use this information in an otherwise classical portfolio optimisation process?

Portfolio optimisation with conditioning information

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

Portfolio optimisation with conditioning information

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);
- risk aversion indices using averaging and normalisation (UBS Investor Sentiment Index 2003) or PCA reduction (Coudert and Gex 2007) of several macroeconomic indicators;

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Portfolio optimisation with conditioning information

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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Theoretical results

Outline



Portfolio optimisation with conditioning information



- Theoretical results
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Theoretical results



- Existing results are useful and instructive but limited to problem variations where a closed-form solution is achievable
- Want to formulate the problem with conditioning information in such a way that more general variations can be tackled (using numerical algorithms if necessary)
- Want to integrate this type of optimisation problem into an existing theoretical framework



- Formulate the Ferson-Siegel problem in optimal control terms
- Use signal (instead of time) as the independent variable and add a signal density factor so integrals in problem represent expectations
- Realise that the signal support may equal all of ℝ and so a doubly-infinite version of the Pontryagin Principle must be available: this is shown in Boissaux and Schiltz (upcoming) along with a doubly-infinite version of the Mangasarian sufficiency theorem

Theoretical results

The portfolio problem in optimal control terms

Minimise

$$J(u) = \int_{s^-}^{s^+} u'(s) \Big[(\mu(s) - r_f e)(\mu(s) - r_f e)' + \Sigma_{\epsilon}^2 \Big] u(s) p_{\mathcal{S}}(s) ds$$

given the state trajectory

$$\dot{x}_1(s) = u'(s)(\mu(s) - r_f e)p_S(s)$$

with

- µ_p unconditional expected portfolio return
- r_f risk-free rate of return
- Σ_{ϵ}^2 conditional covariance matrix
- $p_S(s)$ signal density function

•
$$x_1(s^-) = 0$$
 and $x_1(s^+) = \mu_p - r_f$

• $u(s) \in U \ \forall s$ (asset weights in convex set)

The portfolio problem in optimal control terms(2)

- Assume availability of a risk-free asset with return r_f
- Above expressions are for unconditional variance and expected return in the presence of a signal (modulo constants; see Ferson and Siegel 2001)
- Given a version of the PMP valid on the whole of ℝ, signals with infinite support are covered provided we adapt notation for the boundary conditions
- Formulation corresponds to a variation of a classical LQ minimum energy problem with magnitude constraints (see e.g. Athans and Falb 1966)

Pontryagin Minimum Principle over a doubly-infinite horizon

Theorem

If an admissible pair $(x^*(s), u^*(s))$ is optimal for the above problem, there exist a constant $\lambda_0 \in \{0, 1\}$ and a vector costate function $\lambda(s) = (\lambda_1(s), \dots, \lambda_m(s))$ such that, $\forall s \in (-\infty, \infty)$,

$$(\lambda_0, \lambda_1(\boldsymbol{s}), \dots, \lambda_m(\boldsymbol{s})) \neq (0, 0, \dots, 0),$$

Define the Hamiltonian $\mathcal{H}(x(s), u(s), \lambda_0, \lambda(s), s) = \lambda_0 L(x(s), u(s), s) + \lambda \cdot f(x(s), u(s), s).$ $u^*(s)$ minimises the Hamiltonian over all $u \in U$, i.e. $\forall u \in U, s \in (-\infty, \infty)$, for all admissible pairs (x(s), u(s)),

 $\mathcal{H}(\mathbf{x}^*(\mathbf{s}), \mathbf{u}^*(\mathbf{s}), \lambda_0, \lambda(\mathbf{s}), \mathbf{s}) \leq \mathcal{H}(\mathbf{x}(\mathbf{s}), \mathbf{u}(\mathbf{s}), \lambda_0, \lambda(\mathbf{s}), \mathbf{s})$

Pontryagin Minimum Principle over a doubly-infinite horizon(2)

Theorem

Additionally, the costates λ_i , for $i \in \{1, 2, ..., m\}$, verify

$$\dot{\lambda}_i(s) = -\frac{\partial \mathcal{H}}{\partial x_i}$$

except at any points of discontinuity for $u^*(s)$.

• Similarly, the (standard) Mangasarian sufficiency condition is easily extended to the doubly-infinite case.

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Theoretical results

Open loop optimal portfolio weights

Define the saturation function

$$\operatorname{sat}_{u_i^-, u_i^+}(f_i^*) = \begin{cases} -u_i^+ \text{ if } f_i^* < -u_i^+ \\ f_i^* \text{ if } -u_i^+ < f_i^* < -u_i^- \\ -u_i^- \text{ if } f_i^* > -u_i^-. \end{cases}$$

with $f^{*}(s) = ((\mu(s) - r_{f}e)(\mu(s) - r_{f}e)' + \sum_{\epsilon}^{2})^{-1}(\mu(s) - r_{f}e)\lambda^{*}(s)$ Saturation function example with $u_{i}^{-} < 0$ and $u_{i}^{+} > 0$ u_{i}^{-} u_{i}^{-} u_{i}^{-} u_{i}^{+} u_{i}^{-} u_{i}^{-} u_{i}^{+} u_{i}^{-} u_{i}^{-}

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Theoretical results

Open loop optimal portfolio weights (2)

We get a per-asset expression for the optimal weight:

$$u_i^*(\boldsymbol{s}) = -\operatorname{sat}_{u_i^-, u_i^+}(f_i^*(\boldsymbol{s})),$$

- From the PMP costate equation, the λ^{*}_i(s) = λ^{*}_i are constant
- The optimal weights are piecewise linear in *f** but not, of course, in *s*

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Theoretical results

Classical special cases of problem

- weight limits u^{*}_i(s) → ∞: saturation function becomes identity. We obtain per-asset equations directly yielding costate value and Ferson-Siegel result
- weight limits u^{*}_i(s) → ∞, μ(s) = μ: no informative relationship between signal and return. Formulation yields classical Markowitz solution in closed form.

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Algorithm testing





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Algorithm testing

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Algorithm testing

Data set

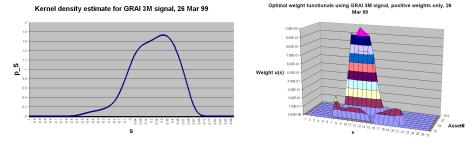
- 11 years of daily data, from January 1999 to February 2010 (2891 samples)
- Risky assets: 10 different EUR-based funds commercialised in Luxembourg chosen across asset categories (equity, fixed income) and across Morningstar style criteria
- Risk-free proxy: EURIBOR with 1 week tenor
- Signal: Kumar and Persaud currency-based GRAI obtained using 3 monthly forward rates

Algorithm testing

Experiment

- Rebalance Markowitz-optimal portfolio alongside portfolio optimal with conditioning information over the 11-year period
- Assume lagged relationship μ(s) between signal and return can be represented by a linear regression
- Use kernel density estimates for signal densities
- Use direct (Gaussian collocation) method for numerical problem solutions (Benson 2005)
- 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), ongoing returns (ex post) of both strategies

Typical kernel density estimate for signal and resulting optimal weight functionals



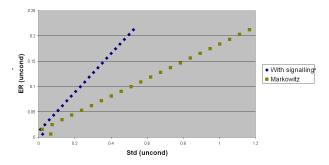
 As would be expected, the constrained optimal weights are not simply a truncated version of the unconstrained optimal (Ferson-Siegel) weights

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Algorithm testing

Typical efficient frontiers using Markowitz portfolios and portfolios using signal information

Example efficient frontiers using both Markowitz optimum and signalling (positive weights, GRAI 3M signal, 26 Mar 99)

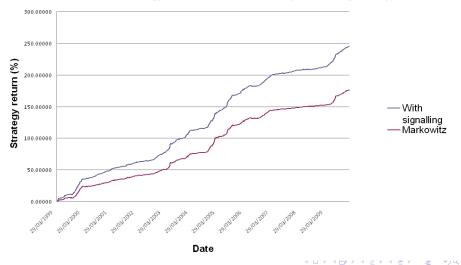


 Average Sharpe ratios over 2891 samples: Markowitz -0.289, using signal - 0.373 (using business daily returns and volatilities)

Algorithm testing

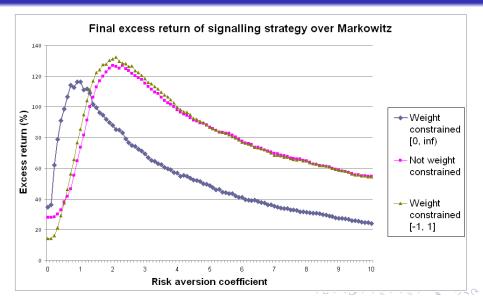
Evolution of strategy returns

Cumulative strategy returns (risk aversion = 3, positive weights only)



Algorithm testing

Comparison of strategy excess returns over Markowitz



Summary

- By using the *signal* as the independent variable, we can express portfolio optimisation problems with conditioning information in an optimal control format
- Necessity and sufficiency results in optimal control theory can easily be generalised to the required doubly-infinite horizon context
- In this way, it becomes possible to solve more general types of optimisation problem through applying any of the numerous numerical optimal control solution approaches available
- The presented problem yields significant outperformance of a pure Markowitz strategy in a more realistic setting than the unconstrained optimum with signalling can afford