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Global Portfolio Optimization: A Least Discrimination Alternative to Black-Litterman

by

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Outline

- **Black-Litterman (BL) Model Revisited**
 - BL assumptions, results and critique
 - BLS: the BL singular case
 - BLC: the BL conditional case
 - Illustration
- **Optimal Pay-offs**
 - Maximum expected utility (EU) pay-off
 - Active pay-off
 - Generalized relative entropy distance (GRE)
- **The Least Discriminatory (LD) Model**
 - The Least Discrimination Principle
 - LD distributions with views on expected returns and covariances

Black-Litterman Revisited

- “Quantitative asset allocation models have not played the important role they should” (Black & Litterman [1992]). Why? They often led to **badly behaved** portfolios (**unrealistic** and **unstable**)
- Practitioners have coped with these problems by using:
 - **Robust estimators** (Jorion [1986]) \Rightarrow priors
 - **Constraints** (Jaggannathan [2003]) \Rightarrow ‘corner’ solutions
 - **Robust optimizer** (Fabozzi [2007]) \Rightarrow conservative MaxMinand/or the

BL seek to improve probabilistic forecasts



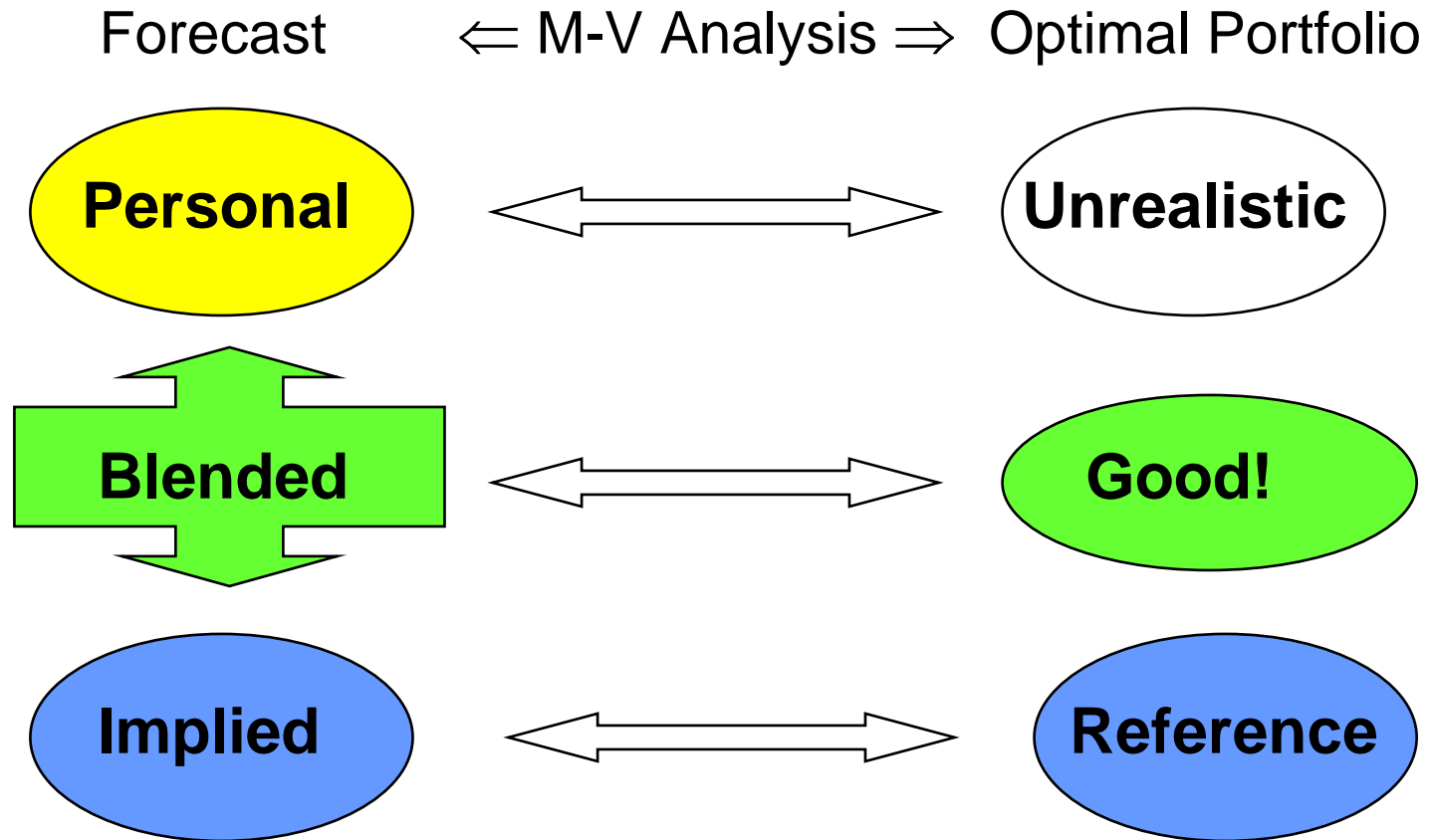
BL Approach

1. Choose a **reference portfolio**
2. Derive a **market implied forecast**
3. **Blend** personal views with market implied forecast

Blending can produce optimal portfolios as close as desired to the reference portfolio

BL blending technique assumes **uncertainties in personal and market implied views of expected returns!!!**

BL Approach



The Market Implied Forecast

Markowitz M-V \Rightarrow
$$\pi = \gamma \Sigma \omega \quad (1)$$

- ω vector of n risky asset allocations in reference portfolio
- Σ covariance matrix; sample estimate from historical data, perhaps adjusted for volatilities implied by option prices
- γ investor's coefficient of risk aversion
- π vector of **expected excess returns implied** by γ , Σ , and ω assuming the **reference portfolio is optimal**.

BL assume that implied expected returns μ are uncertain with mean given by (1) and **covariance matrix $\tau \Sigma$, $\tau < 1$**

$$\mu \sim N(\pi, \tau \Sigma) \quad (2)$$

Personal Views

- Personal views limited to **expected returns on a few assets**
- Views about expected returns μ are expressed by a set of k linear equations

$$\mathbf{P}\mu = \mathbf{q} + \varepsilon \quad (3)$$

- ε represents the uncertainty in the views \mathbf{q} . The components of ε are assumed to be **independently normally distributed**, so that

$$\mathbf{P}\mu \sim N(\mathbf{q}, \mathbf{\Omega}) \quad (4)$$

$\mathbf{\Omega}$ is a diagonal matrix

BL Blending Method

- Combine respective pdfs as if from two **independent sources of information**
- Posterior distribution $\mu \sim N(\mathbf{p}, \mathbf{M})$ has an expected value and a covariance matrix that depend on the assumed uncertainties in each of the two information sources:

$$\mathbf{p} = [\boldsymbol{\Sigma}^{-1} + \mathbf{P}'\tau\boldsymbol{\Omega}^{-1}\mathbf{P}]^{-1} [\boldsymbol{\Sigma}^{-1}\boldsymbol{\pi} + \mathbf{P}'\tau\boldsymbol{\Omega}^{-1}\mathbf{q}] \quad (5)$$

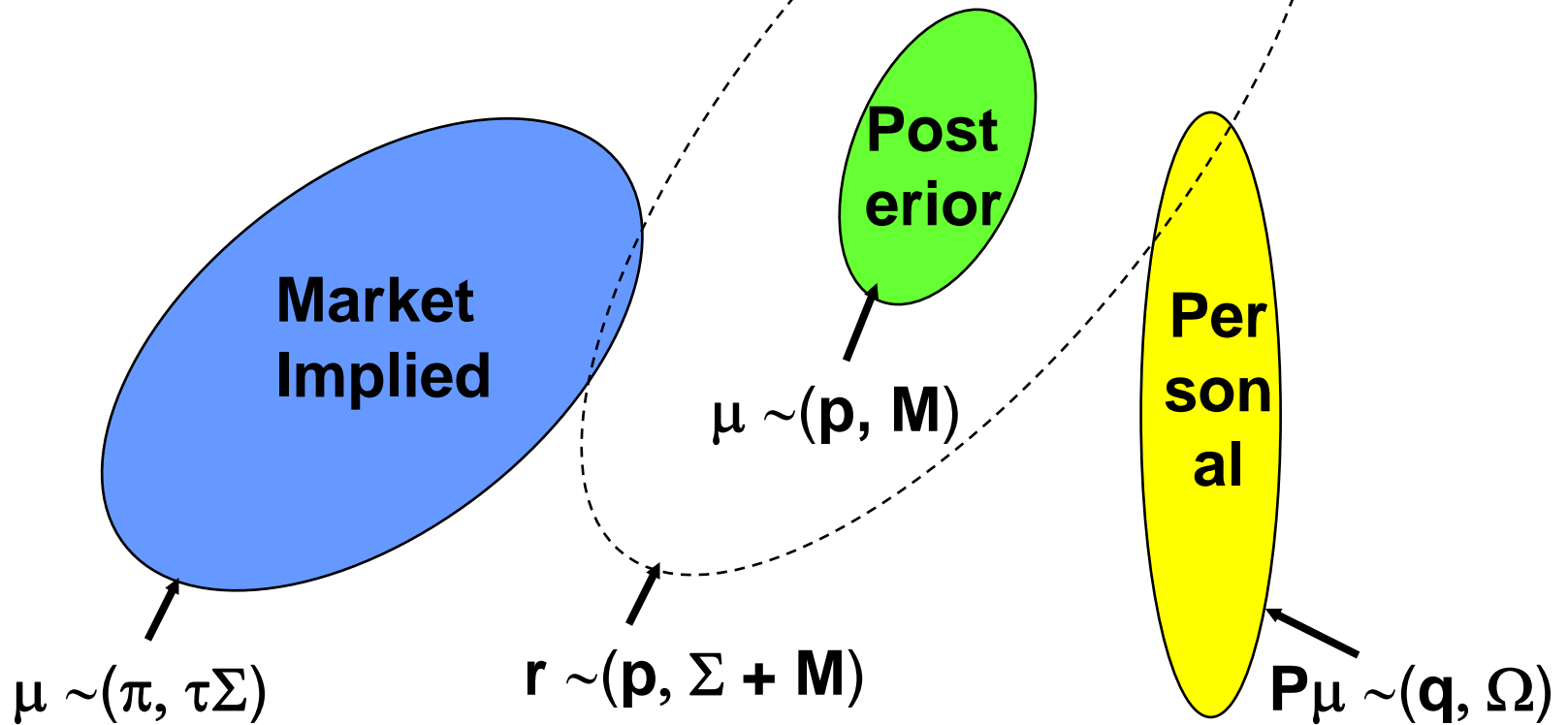
$$\mathbf{M} = \tau[\boldsymbol{\Sigma}^{-1} + \mathbf{P}'\tau\boldsymbol{\Omega}^{-1}\mathbf{P}]^{-1} \quad (6)$$

- Distribution of asset returns:

$$\mathbf{r} \sim N(\mathbf{p}, \boldsymbol{\Sigma} + \mathbf{M}) \quad (7)$$

BL Approach

Expected Returns μ :



Critique of BL

- Uncertainties about expected values?
 - Increase of uncertainty about returns
 - Ad hoc choice of uncertainty parameters $\tau\Sigma$ and Ω
 - Independence between market and personal forecasts
 - Personal views limited to expected returns
 - Two steps in one:
 1. **adjusting** forecast of correlated assets
 2. **blending** with market implied forecast
- ➔ are the results **credible**? Can they be **justified** more logically? Can they be **extended** to other views?

The Singular Case: BLS

Uncertainties in expected returns is only a BL artifice to calculate posterior expected returns

Note that \mathbf{p} and \mathbf{M} in (5) and (6) depend on $\tau\Omega^{-1}$ but not on τ and Ω separately

So, shrink τ and Ω to zero keeping $\tau\Omega^{-1}$ constant: \mathbf{p} remains constant and \mathbf{M} vanishes – the posterior distribution of expected returns becomes **singular**

$\tau\Omega^{-1}$ can be defined in terms of a diagonal matrix of **credibility weights C for personal views**:

$$\tau\Omega^{-1} = \text{Diag}[(\mathbf{P}\Sigma\mathbf{P}')^{-1}]\mathbf{C}(\mathbf{I} - \mathbf{C})^{-1} \quad (8)$$

The conditional case: BLC

When some personal views are held with certainty ($C = 1$ or $\tau\Omega^{-1}$ infinite), the distribution of expected returns becomes the distribution conditional on the views. The posterior expected returns are given by:

$$\mathbf{p} = \boldsymbol{\pi} + \boldsymbol{\Sigma}\mathbf{P}'[\mathbf{P}\boldsymbol{\Sigma}\mathbf{P}']^{-1}[\mathbf{q} - \mathbf{P}\boldsymbol{\pi}] \quad (9)$$

This result can be obtained directly by minimizing the quadratic distance between \mathbf{p} and $\boldsymbol{\pi}$

$$d = (\mathbf{p} - \boldsymbol{\pi})'\boldsymbol{\Sigma}^{-1}(\mathbf{p} - \boldsymbol{\pi})$$

subject to the views on expected returns:

$$\mathbf{P}\boldsymbol{\mu} = \mathbf{q}$$

Illustration of BL, BLS & BLC

MARKET IMPLIED FORECAST

Two risky assets A, B: $\sigma_A = 10\%$, $\sigma_B = 20\%$, $\rho_{AB} = +62.5\%$
(eg. A = G8 equity index, B = BRIC equity index) and a
risk-free asset C

Reference portfolio (M): $\omega_A = \omega_B = 0.5$, $\omega_C = 0$

Risk aversion: $\gamma = 4$

Under BLS

(1) \Rightarrow market implied $\pi_A = 4.5\%$, $\pi_B = 10.5\%$

Under BL, with $\tau = 0.09$: $\sigma_A = 10.44\%$, $\sigma_B = 20.88\%$

(1) \Rightarrow market implied $\pi_A = 4.95\%$, $\pi_B = 11.45\%$

Illustration of BLS & BLC

A PERSONAL VIEW

Expected return $\mu_A = 5.5\%$

Might also be expressed as:

P1: $\mu_A = 5.5\%$ and $\mu_B = 10.5\%$

P2: $\mu_A = 5.5\%$, no view on μ_B

P3: $\mu_B - \mu_A = 5\%$

P4: $11\mu_B - 21\mu_A = 0\%$

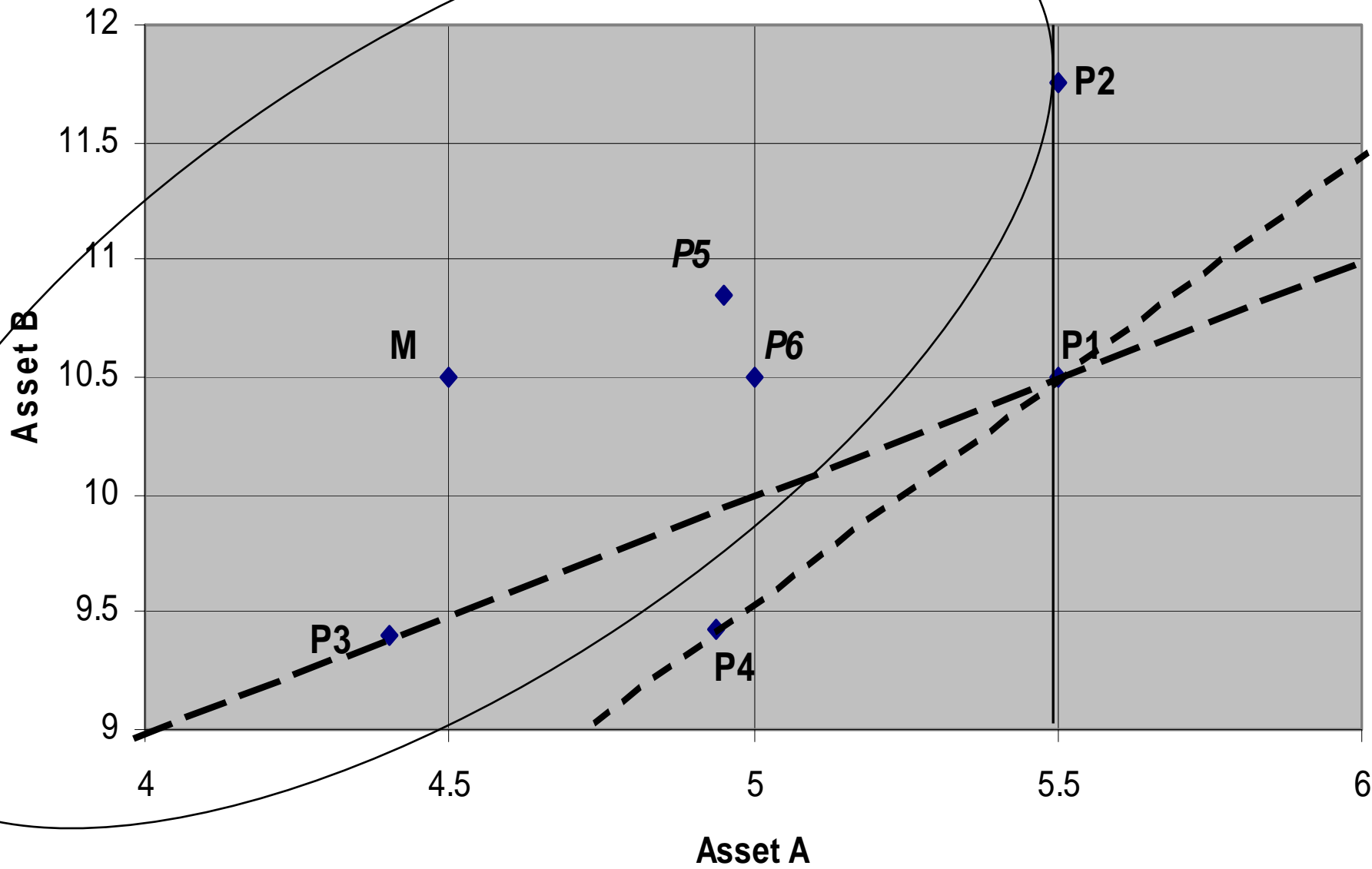
Question: What are the corresponding posterior expected returns and optimal allocations?

Posterior Returns and Optimal Portfolios under BLS & BLC

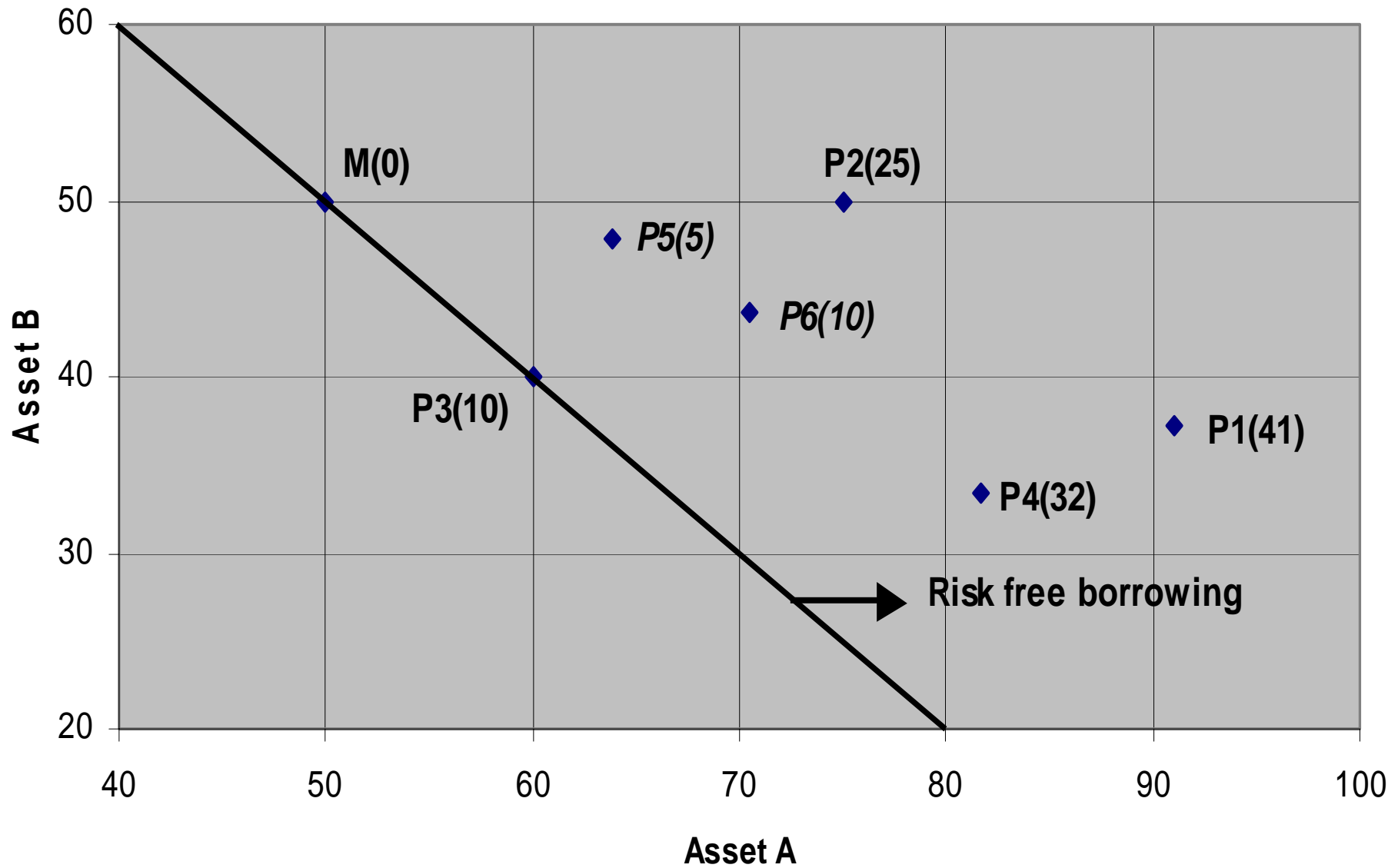
Market (M) and Personal Views (P) in %		Posterior Exp.		Optimal Allocations (%)		
		A	B	A	B	C
M	$\mu_A = 4.5, \mu_B = 10.5$	4.5	10.5	50	50	0
P1	$\mu_A = 5.5, \mu_B = 10.5$	5.5	10.5	91	37.2	-28.2
P2	$\mu_A = 5.5$	5.5	11.75	75	50	-25
P3	$\mu_B - \mu_A = 5.0$	4.4	9.4	60	40	0
P4	$11\mu_B - 21\mu_A = 0$	4.94	9.43	81.7	33.4	-15.1
P5	50% P1 and 50% M	4.95	10.85	63.8	47.8	-11.7
P6	Interpol. (M, P1)	5	10.5	70.5	43.6	-14.1

Results are very sensitive to ways views are expressed

Posterior Expected Returns (%)



Optimal Allocations (%) and CE Gains (bp)



Optimal Pay-offs

Programme:

1. Seek optimal (maximum expected utility) pay-off $f(\mathbf{r} \mid q, p)$ given personal forecast $p(\mathbf{r})$ and risk neutral forecast $q(\mathbf{r})$.
Non-linear pay-offs are generalizations of Markowitz optimal portfolios
2. Evaluate the Certainty Equivalent (CE) of the optimal pay-off \Rightarrow relative entropy distance
3. Evaluate the gain in CE from adding an optimal active pay-off to a reference portfolio \Rightarrow generalized relative entropy distance (GRE)
4. Illustrate with forecasts expressed as multivariate normal distributions (MVN)

Optimal (Maximum EU) Pay-off

Seek pay-off $f(\mathbf{r})$ that maximises the investor's expected utility of wealth at maturity T :

$$\operatorname{argmax}_{f(\cdot)} E_p[u(f(\mathbf{r}) - E_q[f(\mathbf{r})] + w_0)] \quad (10)$$

$p(\mathbf{r})$ personal forecast (subjective probability)

$q(\mathbf{r})$ risk neutral forecast (determines the cost $E_q[f(\mathbf{r})]$ of pay-off $f(\mathbf{r})$)

w_0 investor's initial wealth

$u(\cdot)$ investor's utility function

$E[\cdot]$ expectation operator

Opt. Pay-Off with Exponential $u(\cdot)$

With $u(x) = -\exp(-\gamma x)$, $\gamma =$ coefficient of risk aversion:

$$f(\mathbf{r} | q, p) = [\ln(p(\mathbf{r})/q(\mathbf{r})) + D(q, p)]/\gamma \quad (11)$$

where $D(q, p) = E_q[\ln(q(\mathbf{r})/p(\mathbf{r}))]$ (12)

so that $E_q[f(\mathbf{r} | q, p)] = 0$, i.e., pay-off purchased at par

Pay-off expected utility is $E_p[u(f(\mathbf{r} | q, p))] = -\exp(-D(q, p))$

Therefore, $D(q, p)/\gamma$ is the **certainty equivalent** of the pay-off

$D(q, p)$ is also known as the **relative entropy distance** between pdfs $q(\mathbf{r})$ and $p(\mathbf{r})$.

Optimal Active Pay-off

The reference pay-off $f(\mathbf{r} | q, m)$ is optimal for the market forecast $m(\mathbf{r})$. Pay-off $f(\mathbf{r} | q, p)$ is optimal for personal forecast $p(\mathbf{r})$. By difference the optimal active pay-off is:

$$\begin{aligned} f(\mathbf{r} | q, m, p) &:= f(\mathbf{r} | q, p) - f(\mathbf{r} | q, m) \\ &= (\ln(p(\mathbf{r})/m(\mathbf{r})) + D(q, p) - D(q, m))/\gamma \end{aligned} \quad (13)$$

The **gain in CE from adding the net active pay-off** is:

$$D(q, m, p)/\gamma = (\ln(E_q[p(\mathbf{r})/m(\mathbf{r})]) - E_q[\ln(p(\mathbf{r})/m(\mathbf{r}))])/\gamma \quad (14)$$

$D(q, m, p)$ is a **generalized relative entropy distance**

Optimal Pay-off Illustration

Reference portfolio fully invested in risky asset with $\sigma = 15\%$,
Risk aversion: $\gamma = 4$

Implied expected return $\pi = \gamma\sigma^2\omega = 9\%$

Personal forecast : $p = 8\%$; $s = 20\%$

Optimal pay-off (from (11)):

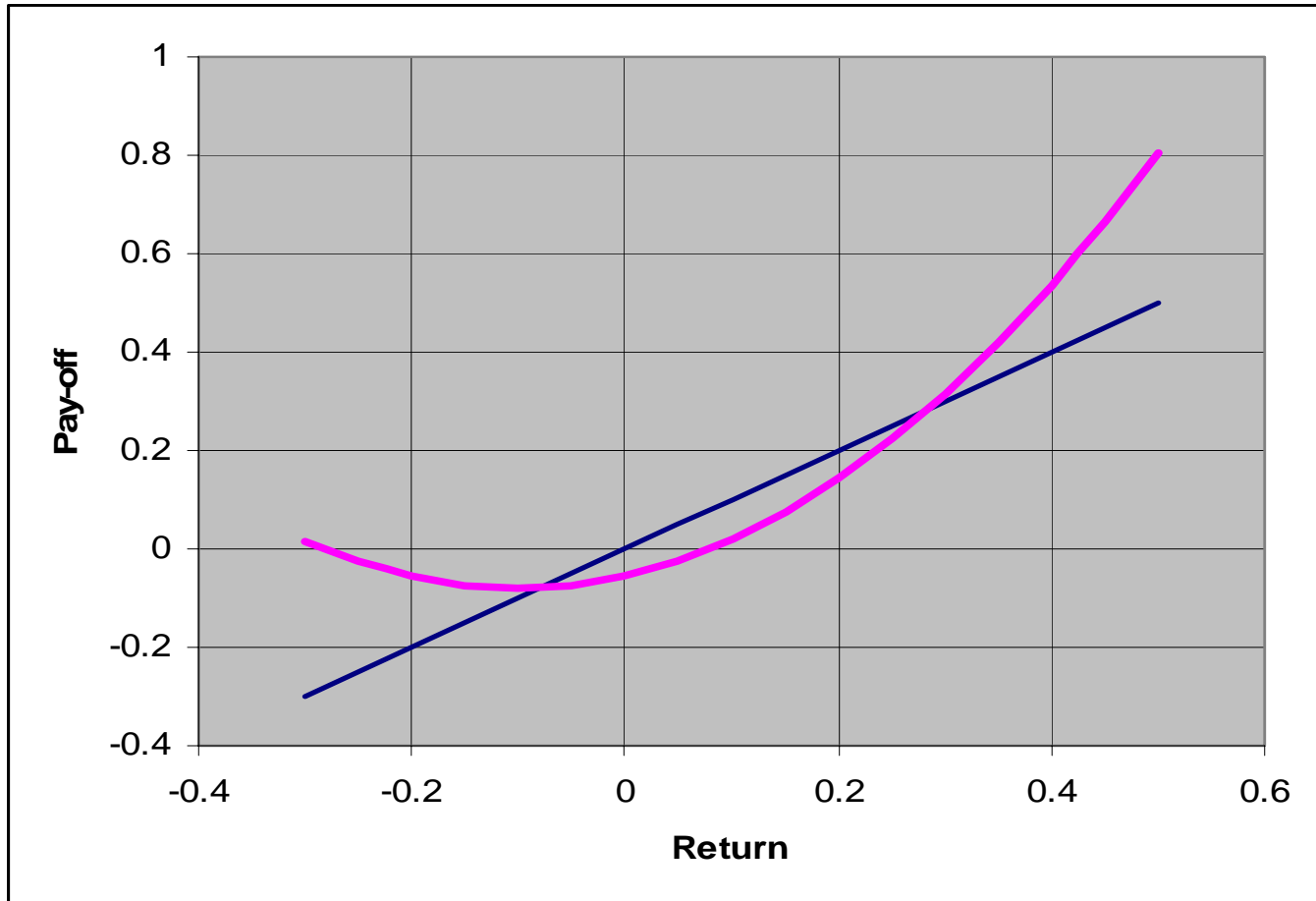
$$f(r | q, p) = (1/2 \gamma)(r^2(\sigma^{-2} - s^{-2}) + 2rps^{-2}) = 2.43(r^2 - 0.0225) + 0.5r$$

Optimal active pay off:

$$f(r | q, m, p) = f(r | q, p) - f(r | q, m) = 2.43(r^2 - 0.0225) - 0.5r$$

The optimal pay-off is quadratic in r . It is an option like pay-off
(approximate with combination of listed options or buy OTC)

Optimal Pay-off Illustration



Least Discrimination (LD) Model

LEAST DISCRIMINATION PRINCIPLE

Among all personal forecasts satisfying a set of views, select the forecast that yields the minimum increase in certainty equivalent when optimally acted upon

Rationale:

Any other forecast would lead to gains in certainty equivalent not supported by personal views and therefore not credible

Calculating LDDs from Views

Given $q(\mathbf{r})$, $m(\mathbf{r})$ and $p(\mathbf{r})$ represented by $N(0, \Sigma)$, $N(\boldsymbol{\pi}, \Sigma)$ and $N(\mathbf{p}, \mathbf{S})$, we seek parameters (\mathbf{p}, \mathbf{S}) for the Least Discriminatory Distribution (LDD) that

Minimise $D(q, m, p)$

subject to (views):

$$\mathbf{P}\mathbf{p} = \mathbf{q} \quad (15)$$

$$\mathbf{G}.\text{Vech}(\mathbf{S}) = \mathbf{h} \quad (16)$$

Hence, minimize the Lagrangian

$$L = D(q, m, p) - \boldsymbol{\lambda}_1'(\mathbf{P}\mathbf{p} - \mathbf{q}) - \boldsymbol{\lambda}_2'(\mathbf{G}.\text{Vech}(\mathbf{S}) - \mathbf{h}) \quad (17)$$



Application to Alternative Investments (AI)

Exhibit 1: Performance of the Portfolio Constituents

Annual Excess Returns	Bond	Equity	RE	Volatility	Comm.	IHF	FoHF	HF	PE
Mean	1.55%	13.03%	17.18%	-69.25%	5.79%	3.27%	4.80%	8.82%	22.75%
Std. Dev.	3.08%	11.09%	11.32%	37.34%	7.73%	3.71%	4.71%	6.16%	17.61%
Skewness	-0.11	0.07	-0.38	0.18	-0.15	-0.09	-0.24	-0.08	-0.06
Excess Kurtosis	0.01	0.07	0.19	0.19	0.01	-0.05	0.08	-0.04	0.02
1-mth autocorrelation	0.10	0.12	-0.28	0.08	-0.03	0.34	0.22	0.26	0.29
Sharpe Ratio	0.50	1.17	1.52	-1.85	0.75	0.88	1.02	1.43	1.29

Based on monthly arithmetic-returns for the period 1 October 2002 to 31 December 2006



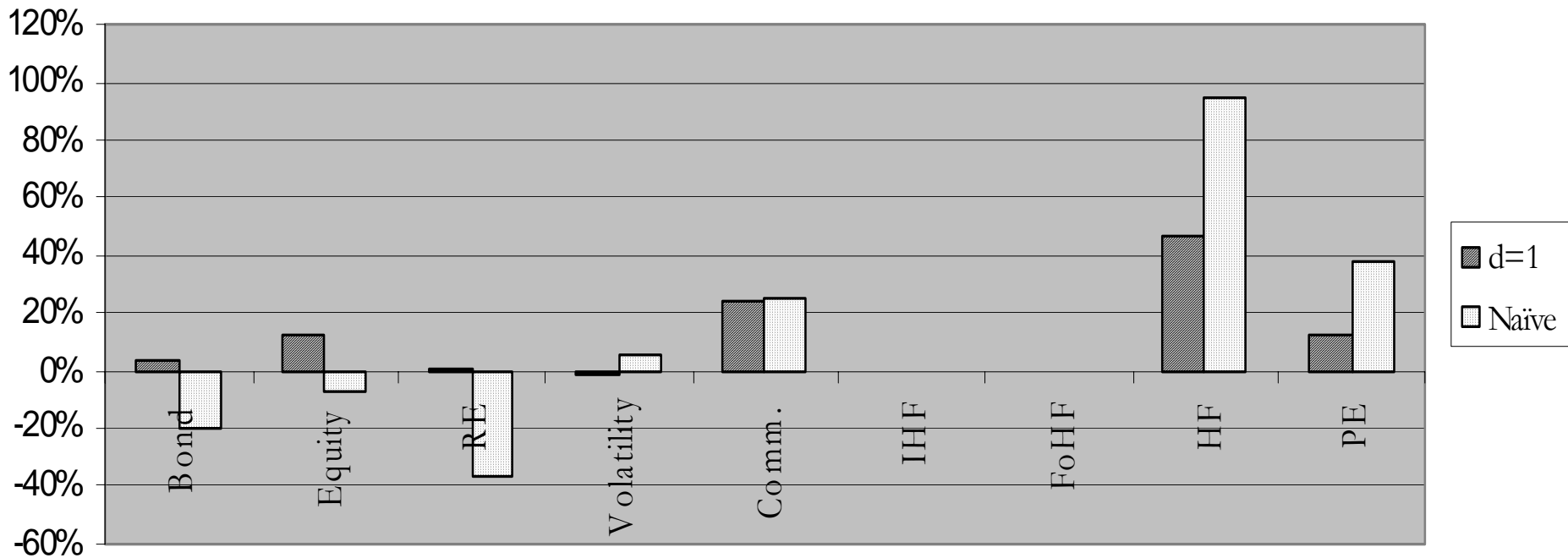
Choice of Forecasts for AI & Traditional Assets

- Choose global market portfolio as reference
- Derive implied expected returns (equilibrium returns)
- Forecast: Use as personal view the average returns observed on AI since October 2002, and for traditional assets use
 - Naïve Scenario – equilibrium returns
 - LD(1) scenario – LD adjusted returns
 - LD(d) Scenarios – blended forecasts with credibility d given to historical forecast of AI and $(1 - d)$ to equilibrium returns

Comparison of Naïve and LD(1) Forecasts

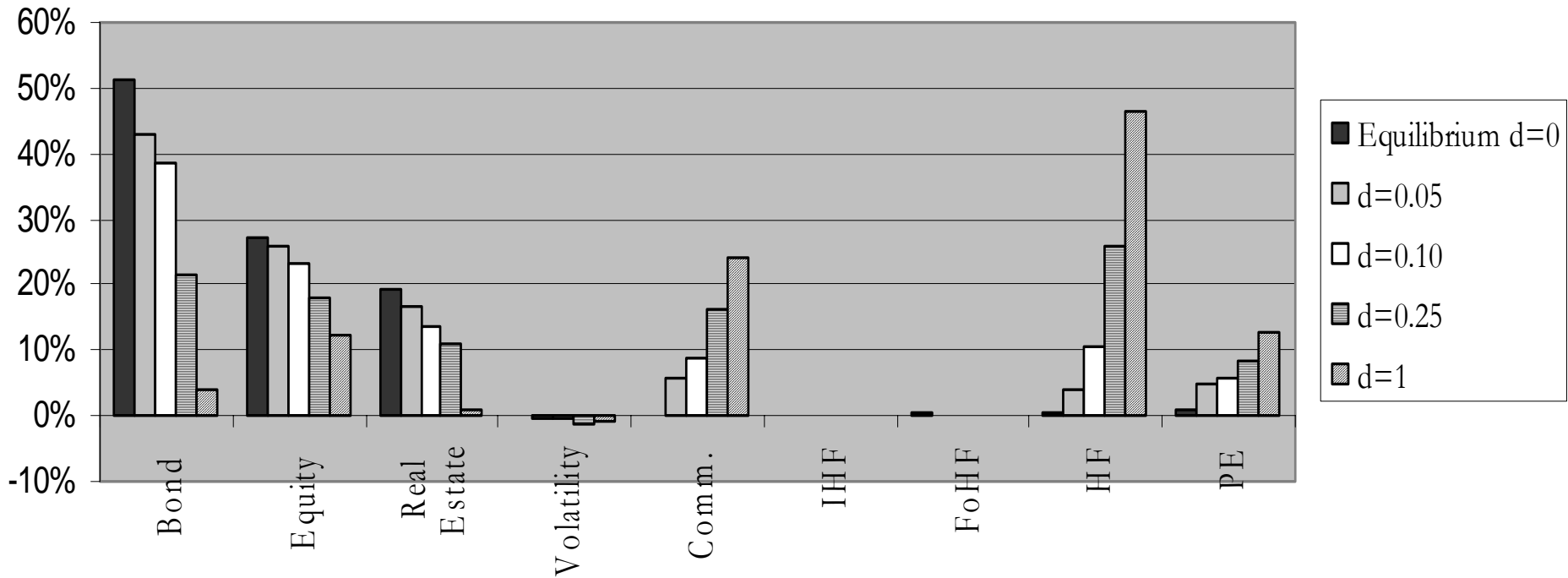


Optimal Allocations for Naïve and LD(1) Subjective Scenarios



Range of Blended LD Forecasts

Optimal Allocations for LD Subjective Scenarios



Summary & Conclusions

- **BL** seek to transform a limited set of personal views into a **complete** and **reasonable probabilistic forecast**
 - But they use questionable assumptions and ad hoc parameters and their method is limited to views on expected returns
 - Use the singular limit, BLS
- The **Least Discrimination principle** offers a **more logical and general** way to achieve the same goal
 - Yields easily optimal portfolios and gains in certainty equivalent
 - With views on covariances, leads to quadratic pay-offs (options)
 - Blending market and personal forecasts still simple
- **Mode of expression of personal views remains critical**

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Appendix:

GRE Between MVN Distributions

When $q(\mathbf{r})$, $m(\mathbf{r})$ and $p(\mathbf{r})$ are represented by $N(0, \Sigma)$, $N(\boldsymbol{\pi}, \Sigma)$ and $N(\mathbf{p}, \mathbf{S})$, respectively, then

$$f(\mathbf{r} \mid q, m, p) = (1/\gamma)(\mathbf{S}^{-1}\mathbf{p} - \Sigma^{-1}\boldsymbol{\pi})'\mathbf{r} \\ - (1/2\gamma) [\mathbf{r}'(\mathbf{S}^{-1} - \Sigma^{-1})\mathbf{r} + n - \text{Tr}(\Sigma\mathbf{S}^{-1})] \quad (\text{A1})$$

and

$$D(q, m, p) = 1/2(\mathbf{p} - \boldsymbol{\pi})'\Sigma^{-1}(\mathbf{p} - \boldsymbol{\pi}) \\ + 1/2 [\mathbf{p}'(\mathbf{S}^{-1} - \Sigma^{-1})\mathbf{p} + \boldsymbol{\pi}'(\Sigma^{-1}\mathbf{S}\Sigma^{-1} - \Sigma^{-1})\boldsymbol{\pi}] \\ + 1/2 [\text{Tr}(\Sigma\mathbf{S}^{-1}) - n - \ln(|\Sigma\mathbf{S}^{-1}|)] \quad (\text{A2})$$

where $\text{Tr}(\cdot)$ denotes a trace and $|\cdot|$ a determinant

Special MVN Case with $S = \Sigma$

When $S = \Sigma$, the terms in square brackets in (A1) and (A2) are nil, therefore the optimal net active portfolio is

$$f(\mathbf{r} | q, m, p) = (1/\gamma) (\mathbf{p} - \boldsymbol{\pi})' \boldsymbol{\Sigma}^{-1} \mathbf{r} \quad (\text{A3})$$

And the corresponding gain in certainty equivalent

$$(1/\gamma)D(q, m, p) = 1/2(\mathbf{p} - \boldsymbol{\pi})'(\gamma\boldsymbol{\Sigma}^{-1})(\mathbf{p} - \boldsymbol{\pi}) \quad (\text{A4})$$

The reference portfolio corresponding to $N(\boldsymbol{\pi}, \boldsymbol{\Sigma})$ is itself

$$f(\mathbf{r} | q, m) = \boldsymbol{\pi}'(\gamma\boldsymbol{\Sigma})^{-1} \mathbf{r} = \boldsymbol{\omega}' \mathbf{r} \quad (\text{A5})$$

with $\boldsymbol{\omega} = (\gamma\boldsymbol{\Sigma})^{-1}\boldsymbol{\pi}$, i.e., same result as with mean variance analysis, and its CE is

$$(1/\gamma)D(q, m) = 1/2\boldsymbol{\pi}'(\gamma\boldsymbol{\Sigma})^{-1}\boldsymbol{\pi} \quad (\text{A6})$$

LDD with Views on Expected Returns Only

With views on expected returns only (condition (15)) and $D(q, m, p)$ given by (A2), we find that the minimum distance is obtained when choosing $S = \Sigma$. The Lagrangian becomes

$$L = 1/2(\mathbf{p} - \boldsymbol{\pi})' \boldsymbol{\Sigma}^{-1}(\mathbf{p} - \boldsymbol{\pi}) - \boldsymbol{\lambda}_1' (\mathbf{P}\mathbf{p} - \mathbf{q}) \quad (\text{A7})$$

and the minimum is obtained when

$$\partial L / \partial \mathbf{p} = \boldsymbol{\Sigma}^{-1}(\mathbf{p} - \boldsymbol{\pi}) - \mathbf{P}' \boldsymbol{\lambda}_1 = 0$$

hence,

$$\mathbf{p} - \boldsymbol{\pi} = \boldsymbol{\Sigma} \mathbf{P}' \boldsymbol{\lambda}_1$$

and

$$\boldsymbol{\lambda}_1 = (\mathbf{P} \boldsymbol{\Sigma} \mathbf{P}')^{-1} (\mathbf{q} - \mathbf{P} \boldsymbol{\pi})$$

so that

$$\mathbf{p} = \boldsymbol{\pi} + \boldsymbol{\Sigma} \mathbf{P}' (\mathbf{P} \boldsymbol{\Sigma} \mathbf{P}')^{-1} (\mathbf{q} - \mathbf{P} \boldsymbol{\pi}) \quad (\text{A8})$$

Precisely the same result as with BLC (9) so imposing BL's choice of uncertainty parameter $\tau \boldsymbol{\Sigma}$ as a necessity

Matching Active Pay-off and CE

The optimal active pay off with views on expected returns only is:

$$f(\mathbf{r} | \mathbf{q}, \mathbf{m}, \mathbf{p}) = (\mathbf{q} - \mathbf{P}\boldsymbol{\pi})'(\mathbf{P}\boldsymbol{\gamma}\boldsymbol{\Sigma}\mathbf{P}')^{-1}\mathbf{P}\mathbf{r} = \boldsymbol{\omega}'\mathbf{r} \quad (\text{A9})$$

It is the linear combination of risky assets with weights:

$$\boldsymbol{\omega} = \mathbf{P}'(\mathbf{P}\boldsymbol{\gamma}\boldsymbol{\Sigma}\mathbf{P}')^{-1}(\mathbf{q} - \mathbf{P}\boldsymbol{\pi}) \quad (\text{A10})$$

The corresponding gain in certainty equivalent is according to (A2):

$$(1/\boldsymbol{\gamma})D(\mathbf{q}, \mathbf{m}, \mathbf{p}) = \frac{1}{2}(\mathbf{q} - \mathbf{P}\boldsymbol{\pi})'(\mathbf{P}\boldsymbol{\gamma}\boldsymbol{\Sigma}\mathbf{P}')^{-1}(\mathbf{q} - \mathbf{P}\boldsymbol{\pi}) \quad (\text{A11})$$

LDD with Views on Covariances

When minimizing the Lagrangian

$$L = D(q, m, p) - \lambda_1'(\mathbf{P}\mathbf{p} - \mathbf{q}) - \lambda_2'(\mathbf{G} \cdot \text{Vech}(\mathbf{S}) - \mathbf{h})$$

with $D(q, m, p)$ given in (A2), we find that whatever optimum parameters are found for \mathbf{S} , they will affect the choice of expected returns \mathbf{p} . Indeed

$$\partial L / \partial \mathbf{p} = \Sigma^{-1}(\mathbf{p} - \boldsymbol{\pi}) + (\mathbf{S}^{-1} - \Sigma^{-1})\mathbf{p} = 0$$

leads to the solution

$$\mathbf{p} = \mathbf{S}\Sigma^{-1}\boldsymbol{\pi} \tag{A12}$$

A view on covariances affects therefore the expected returns that are not specified in addition to affecting other covariances

The resulting optimal pay-offs are quadratic in \mathbf{r}