Dynamic Entropy Pooling: Portfolio Management with Views at Multiple Horizons

Attilio Meucci and Marco Nicolosi

Learn it: http://www.symmys.com/node/831 **(paper and code)**

Live it: Advanced Risk and Portfolio Management® Bootcamp
www.symmys.com/arpm-bootcamp

Agenda

Background

The profit-and-loss (P&L)

The market model

Portfolio construction

Case studies

Background

	Discretionary	Multiperiod	Mkt impact
Grinold ('89)	×	×	×
Black-Litterman ('90)	✓	×	×
Entropy Pooling ('08)	✓	×	×
Davis-Lleo ('13)	×	✓	×
Garleanu-Pedersen ('13)	×	✓	✓
Dynamic Entropy Pooling	✓	✓	✓

- The standard approach to discretionary portfolio management (Black-Litterman, Entropy Pooling) processes subjective views that refer to the distribution of the market at a specific single investment horizon.
- The standard approach to multi-period portfolio management with market impact (Garleanu-Pedersen) processes non-discretionary (systematic) signals
- Dynamic Entropy Pooling is a quantitative approach to perform dynamic portfolio management with discretionary, multi-horizon views

Agenda

Background

The profit-and-loss (P&L)

The market model

Portfolio construction

Case studies

The profit-and-loss (P&L)

- We assume the single-period P&L is a set of exposures multiplied by the increments of the risk drivers over the rebalancing period:

$$\Pi_{t+1} = \boldsymbol{b}_t' \Delta \boldsymbol{X}_{t+1}$$

- The set of risk drivers can be extended to include also external factors that do not affect directly the P&L of the instruments. On such additional factors we can express views that influence the P&L through correlation. The corresponding entries in the exposures vector will be set to zero.

- We assume the single-period P&L is a set of exposures multiplied by the increments of the risk drivers over the rebalancing period:

$$\Pi_{t+1} = \boldsymbol{b}_t' \Delta \boldsymbol{X}_{t+1}$$

- The set of risk drivers can be extended to include also external factors that do not affect directly the P&L of the instruments. On such additional factors we can express views that influence the P&L through correlation. The corresponding entries in the exposures vector will be set to zero.

- Consider an equity share or an index. Then the risk driver is its log-value:

$$X_t = \ln V_t$$

- The P&L of a portfolio with $h_{n,t}$ shares in the *n*-th asset is:

$$\Pi_{t+1} = \sum_n \underbrace{h_{n,t} V_{n,t}}_{b_{n,t}} \times \underbrace{\left(\frac{V_{n,t+1}}{V_{n,t}} - 1\right)}_{\Delta X_{n,t}} \approx \sum_n b_{n,t} \Delta X_{n,t+1}$$

- More in general, in terms of a style/risk linear factor model:

$$\Pi_{t+1} = \sum_k b_{k,t}^{style} \Delta X_{k,t+1}^{style}$$

- We assume the single-period P&L is a set of exposures multiplied by the increments of the risk drivers over the rebalancing period:

$$\Pi_{t+1} = \boldsymbol{b}_t' \Delta \boldsymbol{X}_{t+1}$$

- The set of risk drivers can be extended to include also external factors that do not affect directly the P&L of the instruments. On such additional factors we can express views that influence the P&L through correlation. The corresponding entries in the exposures vector will be set to zero.

- Suppose that the *n*-th asset is a fixed income instrument. Its value at the first order satisfies

$$\Pi_{n,t+1} \approx -\sum_k dv01_{n,k,t} \Delta Y_{k,t+1}$$

where $Y_{k,t}$ is the *k*-th key-rate on the yield curve; $dv01_{n,k,t}$ is the dollar-sensitivity of the *n*-th instrument to $Y_{k,t}$

- Then the P&L due to a set of fixed income instruments is:

$$\Pi_{t+1} \approx \sum_k \underbrace{\left(-\sum_n h_{n,t} dv01_{n,k,t}\right)}_{b_{k,t}} \Delta X_{k,t+1}$$

- We assume the single-period P&L is a set of exposures multiplied by the increments of the risk drivers over the rebalancing period:

$$\Pi_{t+1} = \boldsymbol{b}_t' \Delta \boldsymbol{X}_{t+1}$$

- The set of risk drivers can be extended to include also external factors that do not affect directly the P&L of the instruments. On such additional factors we can express views that influence the P&L through correlation. The corresponding entries in the exposures vector will be set to zero.

- For a stock option, the risk drivers are the log-value of the underlying and the implied volatility $X_t = \ln V_t$ and Σ_t^{impl}

- Then for a portfolio of stock options, the P&L is:

$$\Pi_{t+1} \approx \sum_n \underbrace{h_{n,t} \delta_{n,t} V_{n,t}}_{b_{n,t}^{\delta}} \Delta X_{n,t+1} + \sum_n \underbrace{h_{n,t} \upsilon_{n,t}}_{b_{n,t}^{\sigma}} \Delta \Sigma_{n,t+1}^{impl}$$

where $\delta_{n,t}$ and $\upsilon_{n,t}$ are the delta and vega of the *n*-th option.

Agenda

Background

The profit-and-loss (P&L)

The market model

Portfolio construction

Case studies

- Consider a book of assets driven by a set of $\bar{n}$ risk drivers $\boldsymbol{X}_t$ (interest rates, implied volatility surfaces, log-prices, etc.)

- We assume that the drivers follow a MVOU process:

$$d\boldsymbol{X}_t = (-\boldsymbol{\theta}\boldsymbol{X}_t + \boldsymbol{\mu})\,dt + \boldsymbol{\sigma}d\boldsymbol{W}_t$$

- Choose a set of discrete monitoring dates $t, t+1, \ldots, \bar{t}$

- Stack the process at the monitoring times as follows:

$$\boldsymbol{X}_{t\rightsquigarrow\bar{t}} \equiv \begin{pmatrix} \boldsymbol{X}_t \\ \boldsymbol{X}_{t+1} \\ \cdot \\ \boldsymbol{X}_{\bar{t}} \end{pmatrix}$$

- Then the process is jointly multivariate normal at all times

$$\boldsymbol{X}_{t\rightsquigarrow\bar{t}}|\boldsymbol{i}_t \sim N(\boldsymbol{\mu}_{t\rightsquigarrow\bar{t}}, \boldsymbol{\sigma}^2_{t\rightsquigarrow\bar{t}})$$

- The expectation vector of the is

$$\boldsymbol{\mu}_{t\rightsquigarrow\bar{t}} \equiv \begin{pmatrix} e^{-0\boldsymbol{\theta}}\boldsymbol{x}_t + \left(\mathbb{I}_{\bar{n}} - e^{-0\boldsymbol{\theta}}\right)\boldsymbol{\theta}^{-1}\boldsymbol{\mu} \\ e^{-1\boldsymbol{\theta}}\boldsymbol{x}_t + \left(\mathbb{I}_{\bar{n}} - e^{-1\boldsymbol{\theta}}\right)\boldsymbol{\theta}^{-1}\boldsymbol{\mu} \\ \cdot \\ e^{-(\bar{t}-t)\boldsymbol{\theta}}\boldsymbol{x}_t + \left(\mathbb{I}_{\bar{n}} - e^{-(\bar{t}-t)\boldsymbol{\theta}}\right)\boldsymbol{\theta}^{-1}\boldsymbol{\mu} \end{pmatrix}$$

- The covariance matrix is

$$\boldsymbol{\sigma}^2_{t\rightsquigarrow\bar{t}} \equiv \begin{pmatrix} \boldsymbol{\sigma}^2_0 & \boldsymbol{\sigma}^2_0 e^{-\boldsymbol{\theta}'} & \boldsymbol{\sigma}^2_0 e^{-2\boldsymbol{\theta}'} & \cdot & \boldsymbol{\sigma}^2_0 e^{-(\bar{t}-t)\theta'} \\ e^{-\boldsymbol{\theta}}\boldsymbol{\sigma}^2_0 & \boldsymbol{\sigma}^2_1 & \boldsymbol{\sigma}^2_1 e^{-\boldsymbol{\theta}'} & \cdot & \boldsymbol{\sigma}^2_1 e^{-(\bar{t}-t-1)\boldsymbol{\theta}'} \\ e^{-2\boldsymbol{\theta}}\boldsymbol{\sigma}^2_0 & e^{-\boldsymbol{\theta}}\boldsymbol{\sigma}^2_1 & \boldsymbol{\sigma}^2_2 & & \\ \cdot & & & \cdot & \\ e^{-(\bar{t}-t)\boldsymbol{\theta}}\boldsymbol{\sigma}^2_0 & & & & \boldsymbol{\sigma}^2_{\bar{t}-t} \end{pmatrix}$$

where

$$vec(\underline{\boldsymbol{\sigma}}^2_\tau) \equiv (\boldsymbol{\theta} \oplus \boldsymbol{\theta})^{-1} \left(\mathbb{I}_{\bar{n}^2} - e^{-(\boldsymbol{\theta}\oplus\boldsymbol{\theta})\tau}\right) vec(\boldsymbol{\sigma}^2)$$

We extend the Entropy Pooling approach in Meucci (2010) to the case of multiple horizons

- **The prior**: assume a model for the joint distribution of the process at the monitoring times:

$$\boldsymbol{X}_{t\rightsquigarrow\bar{t}}|\boldsymbol{i}_t \sim f$$

- **The views**: are statements (constraints) on the yet-to-be defined distribution of the process:

$$g \in \mathcal{V}_t$$

- **The posterior**: is the closest distribution to the prior that satisfies the views:

$$\overline{f} \equiv \operatorname{argmin}_{g\in\mathcal{V}_t} \{\mathcal{E}\,(g, f)\}$$

where the "distance" is the relative entropy

$$\mathcal{E}(g,f) \equiv \int g(\boldsymbol{x}_t,\ldots,\boldsymbol{x}_{\bar{t}}) \ln \frac{g(\boldsymbol{x}_t,\ldots,\boldsymbol{x}_{\bar{t}})}{f(\boldsymbol{x}_t,\ldots,\boldsymbol{x}_{\bar{t}})} d\boldsymbol{x}_t \cdots \boldsymbol{x}_{\bar{t}},$$

We extend the Entropy Pooling approach in Meucci (2010) to the case of multiple horizons

- **The prior**: assume a MVOU model for the joint distribution of the process at the monitoring times

$$\boldsymbol{X}_{t\rightsquigarrow\bar{t}}|\boldsymbol{i}_t \sim N(\boldsymbol{\mu}_{t\rightsquigarrow\bar{t}}, \boldsymbol{\sigma}^2_{t\rightsquigarrow\bar{t}})$$

- **The views**: are statements (constraints) on the yet-to-be defined distribution of the process :

$$\mathcal{V}_t : \begin{cases} \mathbb{E}^g_t\{\boldsymbol{v}_{\mu,t}\boldsymbol{X}_{t\rightsquigarrow\bar{t}}\} \equiv \boldsymbol{\mu}_{view;t} \\ \mathbb{C}v^g_t\{\boldsymbol{v}_{\sigma,t}\boldsymbol{X}_{t\rightsquigarrow\bar{t}}\} \equiv \boldsymbol{\sigma}^2_{view;t}. \end{cases}$$

where $\boldsymbol{v}_{\mu,t}$ and $\boldsymbol{v}_{\sigma,t}$ are matrices that defines arbitrary linear combinations of the process at the times for the views.

- **The posterior**: is the closest distribution to the prior that satisfies the views:

$$\overline{f} \equiv \operatorname{argmin}_{g\in\mathcal{V}_t}\left\{\mathcal{E}\left(g,f\right)\right\} \Rightarrow \boldsymbol{X}_{t\rightsquigarrow\bar{t}}|\boldsymbol{i}_t \sim N(\bar{\boldsymbol{\mu}}_{t\rightsquigarrow\bar{t}}, \bar{\boldsymbol{\sigma}}^2_{t\rightsquigarrow\bar{t}})$$

$$\boxed{\boldsymbol{X}_{t\rightsquigarrow\bar{t}}|\boldsymbol{i}_t \sim N(\bar{\boldsymbol{\mu}}_{t\rightsquigarrow\bar{t}}, \bar{\boldsymbol{\sigma}}^2_{t\rightsquigarrow\bar{t}})}$$

- For the expectation, we introduce the pseudo inverse matrix of $\boldsymbol{v}_{\mu,t}$

$$\boldsymbol{v}^+_{\mu,t} \equiv \boldsymbol{\sigma}^2_{t\rightsquigarrow\bar{t}}\boldsymbol{v}'_{\mu,t}(\boldsymbol{v}_{\mu,t}\boldsymbol{\sigma}^2_{t\rightsquigarrow\bar{t}}\boldsymbol{v}'_{\mu,t})^{-1}$$

we define the two complementary projectors:

$$\mathbb{P}_{\mu,t} \equiv (\mathbb{I}_{\bar{n}(\bar{t}-t+1)} - \boldsymbol{v}^+_{\mu,t}\boldsymbol{v}_{\mu,t}) \qquad \mathbb{P}^{\perp}_{\mu,t} \equiv \boldsymbol{v}^+_{\mu,t}\boldsymbol{v}_{\mu,t}$$

Then

$$\boxed{\bar{\boldsymbol{\mu}}_{t\rightsquigarrow\bar{t}} \equiv \mathbb{P}_{\mu,t}\boldsymbol{\mu}_{t\rightsquigarrow\bar{t}} + \mathbb{P}^{\perp}_{\mu,t}(\boldsymbol{v}^+_{\mu,t}\boldsymbol{\mu}_{view;t})}$$

- Similar, for the covariance we introduce the pseudo inverse of $\boldsymbol{v}_{\sigma,t}$

$$\boldsymbol{v}^+_{\sigma,t} \equiv \boldsymbol{\sigma}^2_{t\rightsquigarrow\bar{t}}\boldsymbol{v}'_{\sigma,t}(\boldsymbol{v}_{\sigma,t}\boldsymbol{\sigma}^2_{t\rightsquigarrow\bar{t}}\boldsymbol{v}'_{\sigma,t})^{-1}$$

and the two complementary projectors:

$$\mathbb{P}_{\sigma,t} \equiv \mathbb{I}_{\bar{n}(\bar{t}-t+1)} - \boldsymbol{v}^+_{\sigma,t}\boldsymbol{v}_{\sigma,t} \qquad \mathbb{P}^{\perp}_{\sigma,t} \equiv \boldsymbol{v}^+_{\sigma,t}\boldsymbol{v}_{\sigma,t}$$

Then

$$\boxed{\bar{\boldsymbol{\sigma}}^2_{t\rightsquigarrow\bar{t}} \equiv \mathbb{P}_{\sigma,t}\boldsymbol{\sigma}^2_{t\rightsquigarrow\bar{t}}\mathbb{P}'_{\sigma,t} + \mathbb{P}^{\perp}_{\sigma,t}(\boldsymbol{v}^+_{\sigma,t}\boldsymbol{\sigma}^2_{view;t}(\boldsymbol{v}^+_{\sigma,t})')(\mathbb{P}^{\perp}_{\sigma,t})'}$$

Agenda

Background

The profit-and-loss (P&L)

The market model

Portfolio construction

Case studies

- As in Garleanu and Pedersen (2013), the satisfaction functional is an infinite sum of discounted trade-offs:

$$\overline{\mathbb{S}}_t^{(\gamma,\eta)} \equiv \sum_{s=t}^{\infty} e^{-\lambda(s-t)} [\overline{\mathbb{E}}\{\Pi_{(s,s+1]}|\boldsymbol{i}_t\} - \frac{\gamma}{2}\overline{\mathbb{V}}\{\Pi_{(s,s+1]}|\boldsymbol{i}_t\} - \frac{\eta}{2}\overline{\mathbb{E}}\{MI_s|\boldsymbol{i}_t\}]$$

where the market impact is a quadratic function of the exposure rebalancing

$$MI_t = a^2 + \Delta\boldsymbol{b}_t'\boldsymbol{c}^2\Delta\boldsymbol{b}_t$$

with $\boldsymbol{c}^2$ a suitable positive definite matrix. Note the term a^2, which represents the average cost of maintaining constant exposures

- Given that the P&L is linear in the exposures $\Pi_{t+1} = \boldsymbol{b}_t' \Delta \boldsymbol{X}_{t+1}$, we need to solve for the optimal policy of exposures as functions of information

$$\{\boldsymbol{b}_s^* = p_s^*(\boldsymbol{i}_s)\}_{s \geq t}$$

where

$$\{p_s^*\}_{s \geq t} = \operatorname{argmax}_{\{p_s\}_{s \geq t} \in \mathcal{C}} \overline{\mathbb{E}}_t \{ \sum_{s=t}^{\infty} e^{-\lambda(s-t)} [p_s(\boldsymbol{I}_s)' \boldsymbol{\omega}\, \overline{\mathbb{E}}_s \{\Delta \boldsymbol{X}_{s+1}\} - \frac{\gamma}{2} p_s(\boldsymbol{I}_s)' \boldsymbol{\omega} \overline{\mathbb{C}} v_s \{\Delta \boldsymbol{X}_{s+1}\} \boldsymbol{\omega}' p_s(\boldsymbol{I}_s) - \frac{\eta}{2} \Delta p_s(\boldsymbol{I}_s)' \boldsymbol{c}^2 \Delta p_s(\boldsymbol{I}_s)] \}$$

- As in Garleanu and Pedersen (2013), the satisfaction functional is an infinite sum of discounted trade-offs:

$$\overline{\mathbb{S}}_t^{(\gamma,\eta)} \equiv \sum_{s=t}^{\infty} e^{-\lambda(s-t)} [\overline{\mathbb{E}} \{\Pi_{(s,s+1]} | \boldsymbol{i}_t\} - \frac{\gamma}{2} \overline{\mathbb{V}} \{\Pi_{(s,s+1]} | \boldsymbol{i}_t\} - \frac{\eta}{2} \overline{\mathbb{E}} \{MI_s | \boldsymbol{i}_t\}]$$

where the market impact is a quadratic function of the exposure rebalancing

$$MI_t = a^2 + \Delta \boldsymbol{b}_t' \boldsymbol{c}^2 \Delta \boldsymbol{b}_t$$

with $\boldsymbol{c}^2$ a suitable positive definite matrix. Note the term a^2, which represents the average cost of maintaining constant exposures

- Given that the P&L is linear in the exposures $\Pi_{t+1} = \boldsymbol{b}_t' \Delta \boldsymbol{X}_{t+1}$, we need to solve for the optimal policy of exposures as functions of information

$$\{\boldsymbol{b}_s^* = p_s^*(\boldsymbol{i}_s)\}_{s\geq t}$$

where

$$\{p_s^*\}_{s\geq t} = \operatorname{argmax}_{\{p_s\}_{s\geq t}\in\mathcal{C}} \overline{\mathbb{E}}_t\{\textstyle\sum_{s=t}^{\infty} e^{-\lambda(s-t)}[p_s(\boldsymbol{I}_s)'\boldsymbol{\omega}\,\overline{\mathbb{E}}_s\{\Delta\boldsymbol{X}_{s+1}\} - \frac{\gamma}{2}p_s(\boldsymbol{I}_s)'\boldsymbol{\omega}\overline{\mathbb{C}}v_s\{\Delta\boldsymbol{X}_{s+1}\}\boldsymbol{\omega}'p_s(\boldsymbol{I}_s) - \frac{\eta}{2}\Delta p_s(\boldsymbol{I}_s)'\boldsymbol{c}^2\Delta p_s(\boldsymbol{I}_s)]\}$$

- Dynamic programming with a quadratic value function yields a recursive problem with time-dependent coefficients

$$v_{s+1}(\boldsymbol{b}_s,\boldsymbol{x}_{s+1}) = -\tfrac{1}{2}\boldsymbol{b}_s'\boldsymbol{\psi}_{bb,s}\boldsymbol{b}_s + \boldsymbol{b}_s'\boldsymbol{\psi}_{bx,s}\boldsymbol{x}_{s+1} + \tfrac{1}{2}\boldsymbol{x}_{s+1}'\boldsymbol{\psi}_{xx,s}\boldsymbol{x}_{s+1} + \boldsymbol{\psi}_{b,s}'\boldsymbol{b}_s + \boldsymbol{\psi}_{x,s}'\boldsymbol{x}_{s+1} + \psi_{0,s}$$

$$\Longleftrightarrow \quad \boldsymbol{\psi}_{s-1} = g_s(\boldsymbol{\psi}_s)$$

- The optimal policy of exposures then reads

$$\boldsymbol{b}_s^* = (\gamma\boldsymbol{\omega}\bar{\boldsymbol{\sigma}}_s^2\boldsymbol{\omega}' + \eta\boldsymbol{c}^2 + e^{-\lambda}\boldsymbol{\psi}_{bb,s})^{-1}[\underbrace{\eta\boldsymbol{c}^2\boldsymbol{b}_{s-1}}_{\text{legacy exposures}} + \underbrace{(\boldsymbol{\omega}\boldsymbol{\beta}_s + e^{-\lambda}\boldsymbol{\psi}_{bx,s}(\boldsymbol{\beta}_s + \mathbb{I}_{\bar{n}}))\boldsymbol{x}_s}_{\text{current risk drivers}} + \underbrace{(\boldsymbol{\omega} + e^{-\lambda}\boldsymbol{\psi}_{bx,s})\boldsymbol{\alpha}_s + e^{-\lambda}\boldsymbol{\psi}_{b,s}}_{(\star)\text{ future views}}]$$

- Given that the P&L is linear in the exposures $\Pi_{t+1} = \boldsymbol{b}'_t \Delta \boldsymbol{X}_{t+1}$, we need to solve for the optimal policy of exposures as functions of information

$$\{\boldsymbol{b}^*_s = p^*_s(\boldsymbol{i}_s)\}_{s\geq t}$$

where

$$\{p^*_s\}_{s\geq t} = \operatorname{argmax}_{\{p_s\}_{s\geq t}\in\mathcal{C}} \overline{\mathbb{E}}_t\{ \textstyle\sum_{s=t}^{\infty} e^{-\lambda(s-t)} [p_s(\boldsymbol{I}_s)'\boldsymbol{\omega}\, \overline{\mathbb{E}}_s\{\Delta\boldsymbol{X}_{s+1}\} - \frac{\gamma}{2} p_s(\boldsymbol{I}_s)'\boldsymbol{\omega}\overline{\mathbb{C}}v_s\{\Delta\boldsymbol{X}_{s+1}\}\boldsymbol{\omega}' p_s(\boldsymbol{I}_s) - \frac{\eta}{2}\Delta p_s(\boldsymbol{I}_s)'\boldsymbol{c}^2\Delta p_s(\boldsymbol{I}_s)]\,\}$$

- With no market impact, we obtain a series of myopic one-period problems
- The optimal policy is a sequence of mean-variance optimizations based on the <u>posterior distribution</u> of the risk drivers process

$$\boldsymbol{b}^*_s = \underbrace{\frac{1}{\gamma}(\boldsymbol{\omega}\bar{\boldsymbol{\sigma}}^2_s\boldsymbol{\omega}')^{-1}\boldsymbol{\omega}(\mathbb{P}_{\mu,s})_{s+1,\cdot}\Delta\boldsymbol{\mu}^{LongTerm}_{s\rightsquigarrow\bar{t}}}_{\boldsymbol{b}^{LongTerm}_s} \longleftarrow \begin{pmatrix} \mathbb{I}_{\bar{n}} - e^{-0\boldsymbol{\theta}} \\ \mathbb{I}_{\bar{n}} - e^{-1\boldsymbol{\theta}} \\ \vdots \\ \mathbb{I}_{\bar{n}} - e^{-(\bar{t}-s)\boldsymbol{\theta}} \end{pmatrix} (\boldsymbol{\theta}^{-1}\boldsymbol{\mu} - \boldsymbol{x}_s)$$

$$+ \underbrace{\frac{1}{\gamma}(\boldsymbol{\omega}\bar{\boldsymbol{\sigma}}^2_s\boldsymbol{\omega}')^{-1}\boldsymbol{\omega}(\mathbb{P}^{\perp}_{\mu,s})_{s+1,\cdot}\Delta\boldsymbol{\mu}^{ViewMean}_{s\rightsquigarrow\bar{t}}}_{\boldsymbol{b}^{ViewMean}_s} \longleftarrow \boldsymbol{v}^{+}_{\mu,s}\boldsymbol{\mu}_{view;s} - \boldsymbol{x}_s$$

Agenda

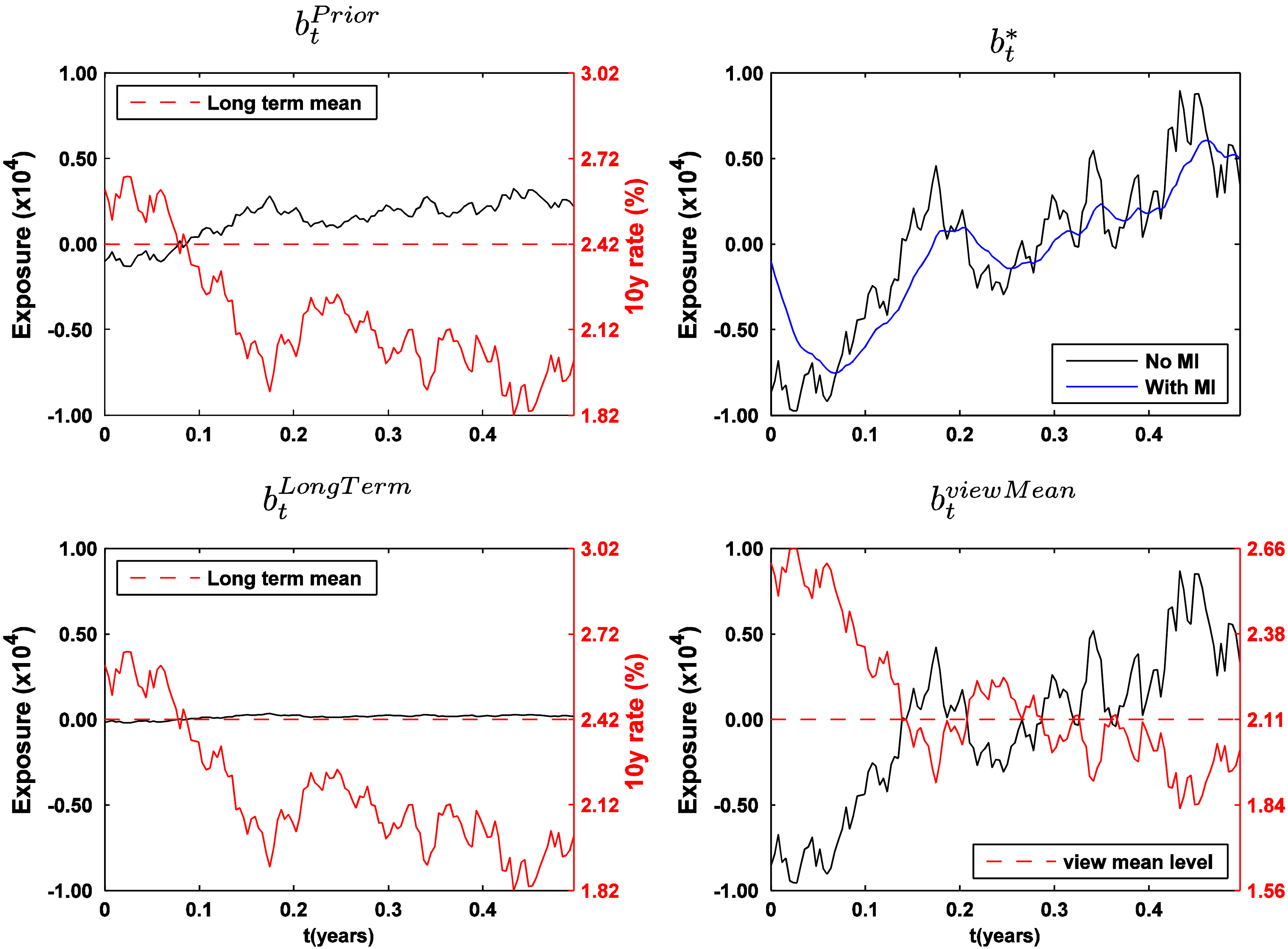
Background

The profit-and-loss (P&L)

The market model

Portfolio construction

Case studies


b_t^{Prior}
Long term mean
Exposure (x10^4)
10y rate (%)
1.00
0.50
0.00
-0.50
-1.00
3.02
2.72
2.42
2.12
1.82
0
0.1
0.2
0.3
0.4
b_t^*
No MI
With MI
$b_t^{LongTerm}$
t(years)
$b_t^{viewMean}$
view mean level
2.66
2.38
2.11
1.84
1.56

Two risk drivers (one investable), two views