Daily vs. Monthly returns

Empirical evidence from Commodity Trading Advisors

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Outline

- The problem
- The CTA industry
- The data set
- Daily vs. Monthly
- Pricing of fund-linked products
Problem description

Hedge funds market themselves through monthly data but in a managed account it is possible to follow a hedge fund investment every day.

*How will the daily risk and quantitative properties experienced by the investor differ from what they expect from the monthly figures?*
Commodity Trading Advisors

CTA - Managed futures industry

- A 30-year-old asset class
- Chartists and trend followers
- Business legend - Turtle traders
Industry figures

BarclayHedge CTA database collects monthly data for CTA programs. Figures from 2010 Q1 shows:

▶ 1058 funds totally over 20 years
▶ Annual return 11.6%, Sharpe ratio 0.41
▶ 553 active funds managing $217.2B
▶ Systematic programs constitute the main part, $169.31B
The data set

- Daily return series from 77 CTA funds of which 65 were active
- No proforma, only live trading
- At least 2 years track record
- Mainly classic CTA strategies, mid- to -long term trend following
Common hedge fund return biases

- Instant history/Back-fill
  - *Start many funds, keep only the profitable, do not report until good live performance and use back-fill possibilities.*
Common hedge fund return biases

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  - *Start many funds, keep only the profitable, do not report until good live performance and use back-fill possibilities.*

- Selection bias
  - *Database reporting is voluntary, causing a self-selection bias*
Common hedge fund return biases

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- Selection bias
  - Database reporting is voluntary, causing a self-selection bias

- Survivorship bias
  - Only the fittest survives, blow-ups are rarely reported
### Moments

<table>
<thead>
<tr>
<th></th>
<th>Daily</th>
<th>Monthly</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean return</td>
<td>Min</td>
</tr>
<tr>
<td>Daily</td>
<td>-0.000178</td>
<td>0.000566</td>
</tr>
<tr>
<td></td>
<td>0.00242</td>
<td>0.010767</td>
</tr>
<tr>
<td></td>
<td>-1.235</td>
<td>-0.1447</td>
</tr>
<tr>
<td></td>
<td>3.7552</td>
<td>9.4731</td>
</tr>
<tr>
<td></td>
<td>0.0038</td>
<td>0.0123</td>
</tr>
<tr>
<td></td>
<td>0.0109</td>
<td>0.0501</td>
</tr>
<tr>
<td></td>
<td>-0.9147</td>
<td>0.2686</td>
</tr>
<tr>
<td></td>
<td>1.8328</td>
<td>4.0179</td>
</tr>
</tbody>
</table>

**Table:** Properties of the first four moments for all managers as a group.
Non-normality

Figure: *Left:* Normal probability plot of returns clearly showing the occurrence of fat tails. *Right:* Empirical distribution (blue) using a Epanechnikov kernel, together with a fitted normal distribution (red)
## Statistical tests

<table>
<thead>
<tr>
<th>Test</th>
<th>Daily</th>
<th>Monthly</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jacque-Berra test</td>
<td>100%</td>
<td>20%</td>
</tr>
<tr>
<td>Lilliefors test</td>
<td>99%</td>
<td>14%</td>
</tr>
<tr>
<td>Lags 1</td>
<td>1</td>
<td>10</td>
</tr>
<tr>
<td>Ljung-Box on returns</td>
<td>50%</td>
<td>50%</td>
</tr>
<tr>
<td>Ljung-Box on absolute returns</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>ARCH-test</td>
<td>90%</td>
<td>97.5%</td>
</tr>
</tbody>
</table>

**Table**: Percentage of funds rejecting the null hypothesis for statistical tests on daily and monthly figures.
Autocorrelation

Figure: Left: Autocorrelation function for log-returns. Right: Autocorrelation for the absolute value of the log-returns. Absolute values show an irrefutable correlation, pointing towards the existence of volatility clustering.
Pricing of fund-linked products

To illustrate the effect of non-normal higher moments we construct simulation examples using a Normal inverse Gaussian distribution:

\[ \text{d}S_t = (\mu + \beta \sigma^2(t))S_t \text{d}t + \sigma(t)S_t \text{d}B_t, \quad S_0 = s > 0, \]
\[ \text{d}\sigma_t^2 = -\lambda \sigma_t^2 \text{d}t + \text{d}L_{\lambda t}, \quad \sigma_0^2 = y > 0, \]

\( B_t \) - Brownian motion, \( L_{\lambda t} \) - pure jump subordinator.
Fixed threshold products

Figure: Fixed threshold product over a five years horizon. **Left:** Rate of the fund investment hitting the barrier for a range of barrier values. **Right:** Percentage increased risk of hitting the barrier when using a NIG-distribution instead of a normal distribution.
Figure: Constant proportion portfolio insurance product simulated over five years for different insurance levels and leverage factor 4. The expected result at expiry is clearly lower for a product simulated using high order moments.