

Asset Management Strategies: Fat Tails and Risk Control

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Acknowledgements

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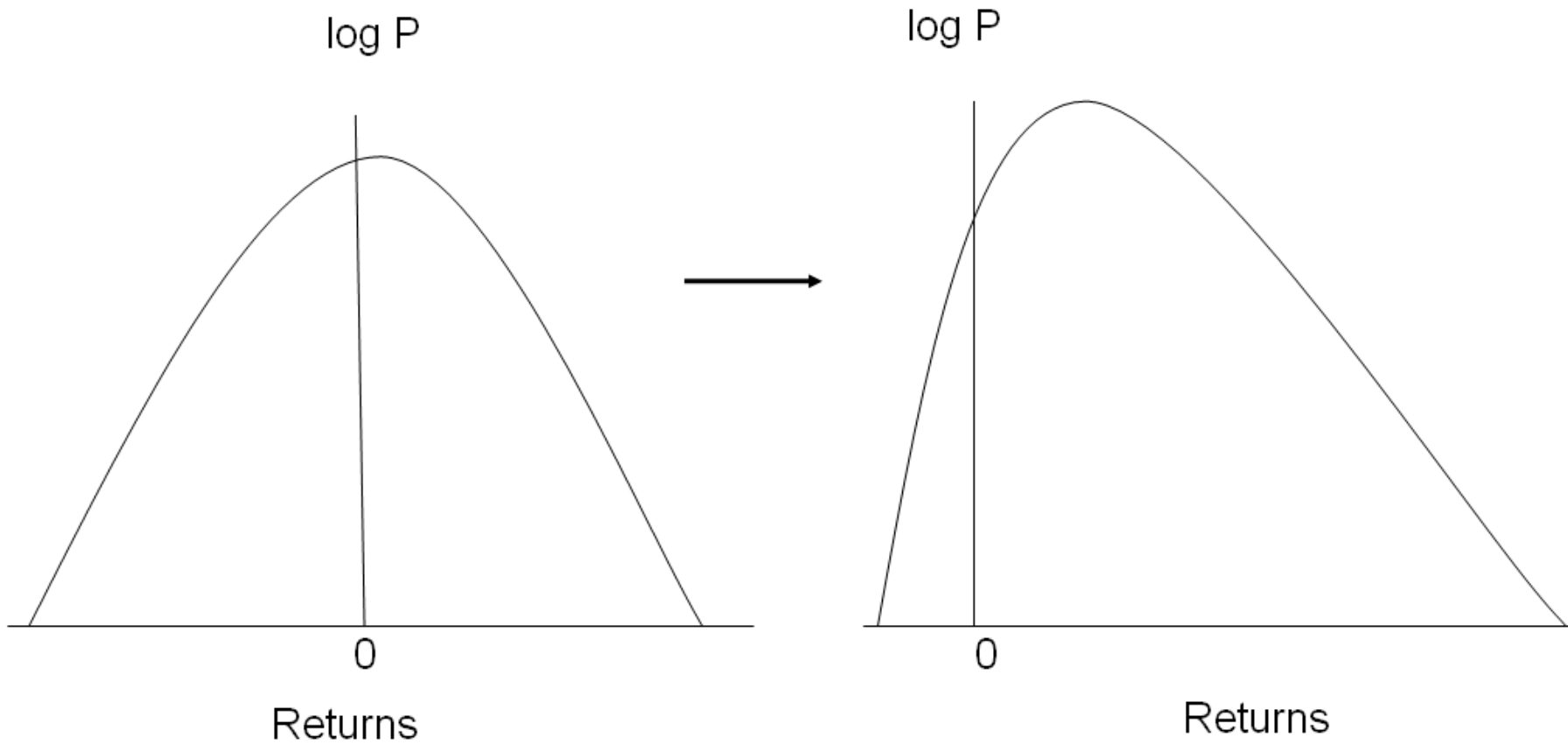
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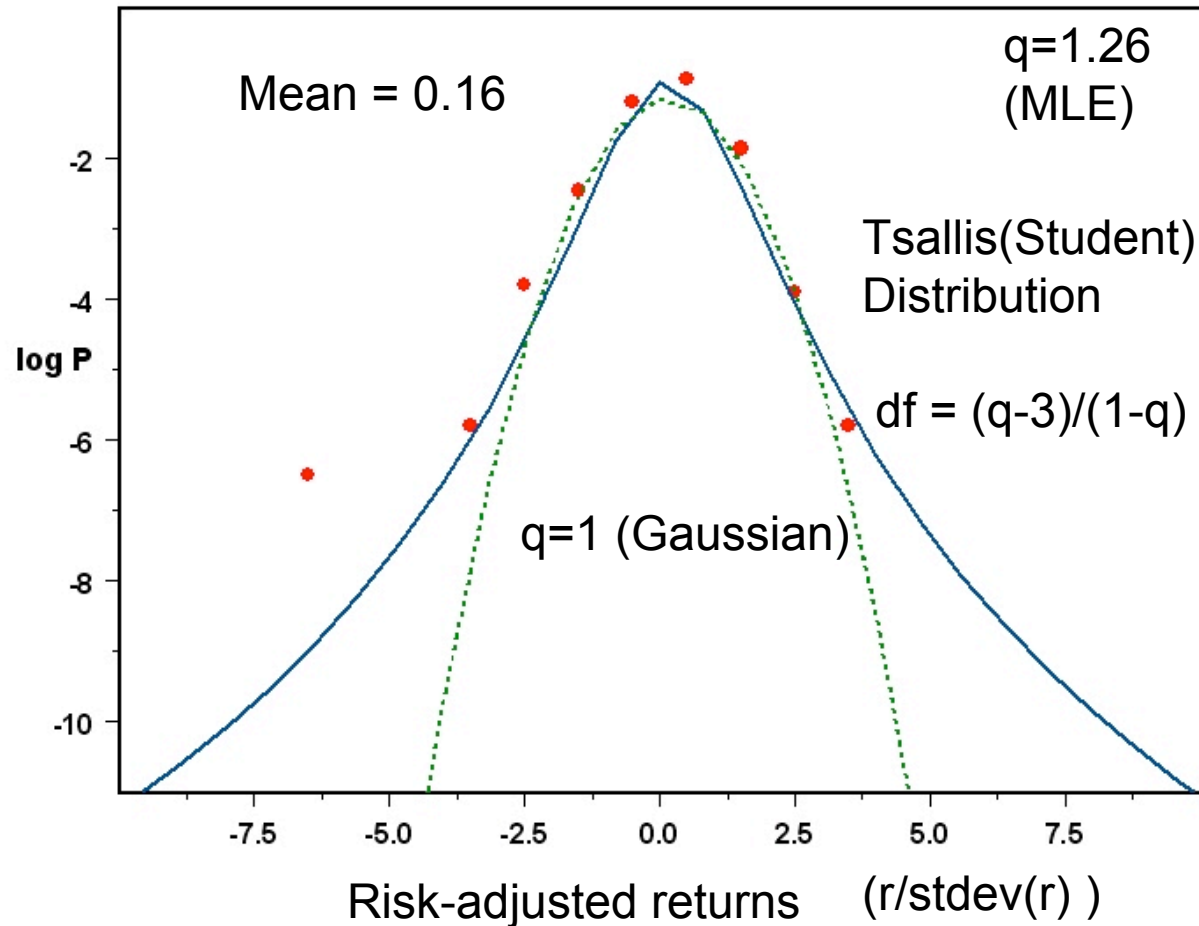
Layout

- Hedge Fund Returns: Distributional Characteristics
- How to Calculate Robust VaR Numbers
- Portfolio Construction in the presence of fat tails



Ideally: A trading strategy transforms underlying asset return distribution favorably

Distribution of S&P 500 Monthly Returns 1951-2007

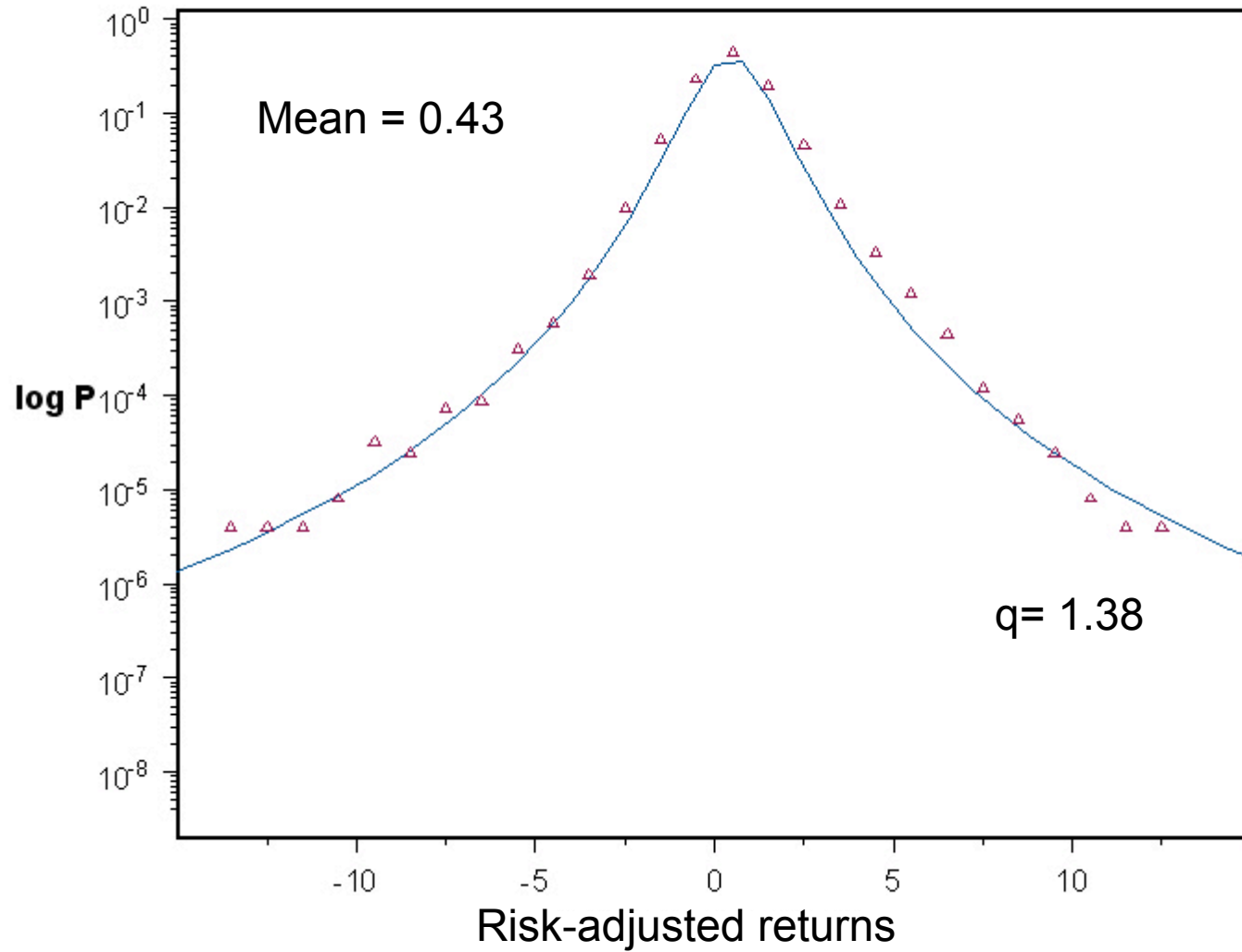


Tsallis distribution: Fits well to daily returns also with $q = 1.4$.

Used for non-Gaussian option pricing
[Borland 2002, Borland & Bouchaud 2004].

Lipper TASS Database: 2883 Funds, 1300 Funds of Funds, Monthly Returns

Hedge Fund Returns



- Hedge Fund managers do shift the mean from 0.16 to 0.43
- Tails are much fatter, monthly returns well-fit by $q=1.4$
- The “ideal” distribution (small left tail) is not achieved, but also no significant negative skew

- $q = 1.3 - 1.5$ fits well to hedge fund monthly returns
- How can we use this for
 - Risk Control
 - Portfolio Construction

VaR

- 5% VaR: You have a 5% chance of getting returns less than VaR (per \$)
- Common calculation methods:
 - Assume a distribution (eg. Gaussian)
 - Use the past N days historical price changes
 - Use MC simulations of future returns

VaR

- 5% VaR: You have a 5% chance of getting returns less than VaR (per \$)
- Common calculation methods:
 - Assume a distribution (eg. Gaussian)
Can't be good! Fat tails!
 - Use the past N days historical price changes
Simple. Can we do better?
 - Use MC simulations of future returns
Very compute-intensive!

Robust Calculation of VaR

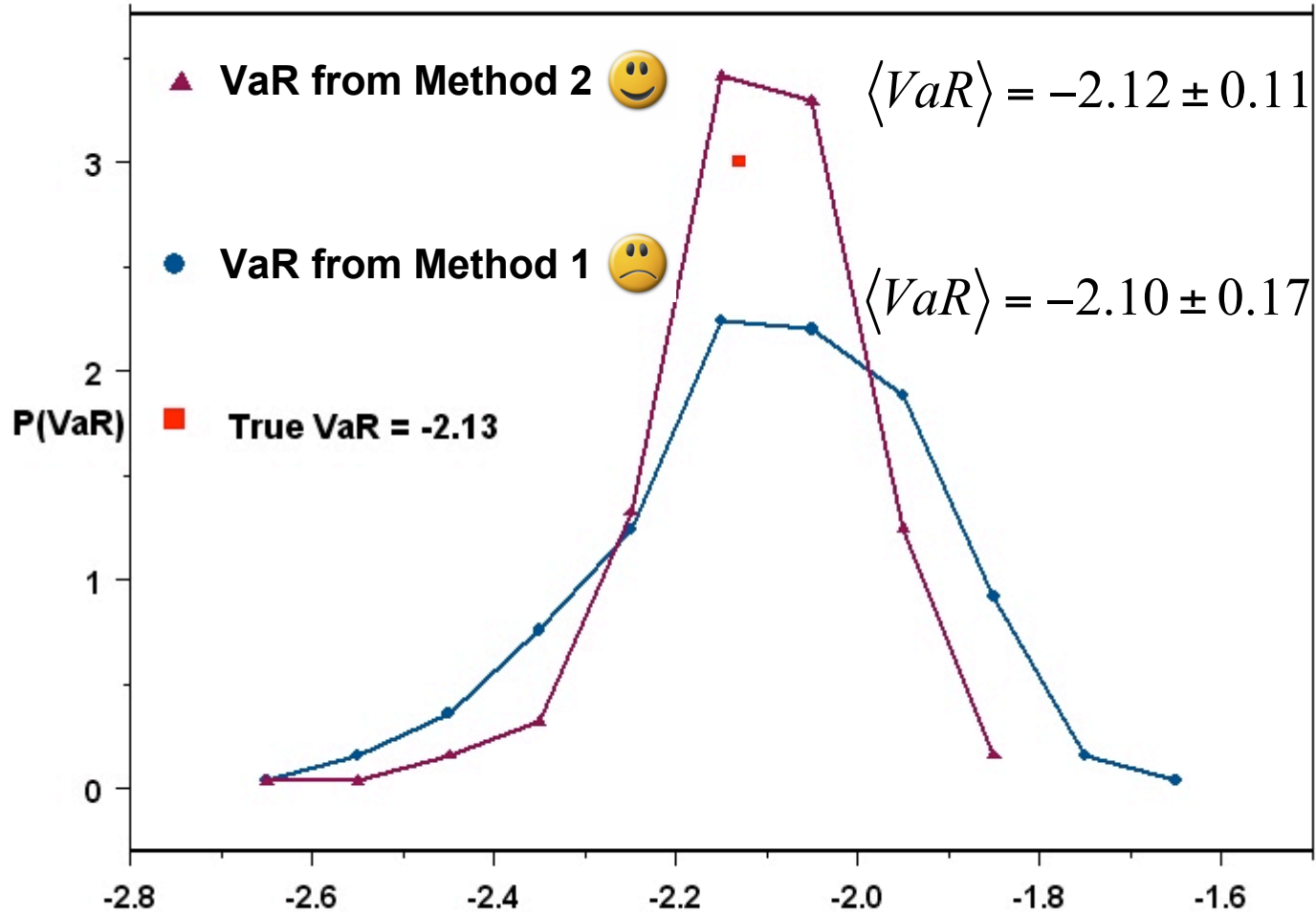
An experiment:

- Simulate 500 returns drawn from $q = 1.4$ Tsallis distribution. Repeat 250 times.
- For each sample:

Method 1: Estimate 5%-ile from 500 day generated data \rightarrow 250 values of VaR.

Method 2: Fit Tsallis distribution of index q to 500 day generated data. Then calculate 5%-ile of that fitted distribution \rightarrow 250 values of VaR.

Robust Calculation of VaR (Example 5%)



- Fitting Tsallis distribution to data and then calculating VaR → More robust estimate
- Using $q=1.4$ is a better prior than the Gaussian distribution
- Better than unconditional VaR using historical data (recent history might be anomalous)

Portfolio construction in the presence of fat-tails

- Single strategy case:

How to calculate optimal holdings?

One strategy is:

Maximize expected long-run profit based on log-utility function (Kelly criterion)

$$\left\langle \log(1 + hx) \right\rangle_{P(x|\mu, \sigma)}$$

h = holding (position size)

μ = expected return

σ = standard deviation (volatility)

q-Kelly criterion

$$\int \log(1 + hx) N \left(1 + (q - 1) \frac{(x - \mu)^2}{\sigma^2} \right)^{\frac{1}{1-q}} dx$$

Gaussian, $q=1$

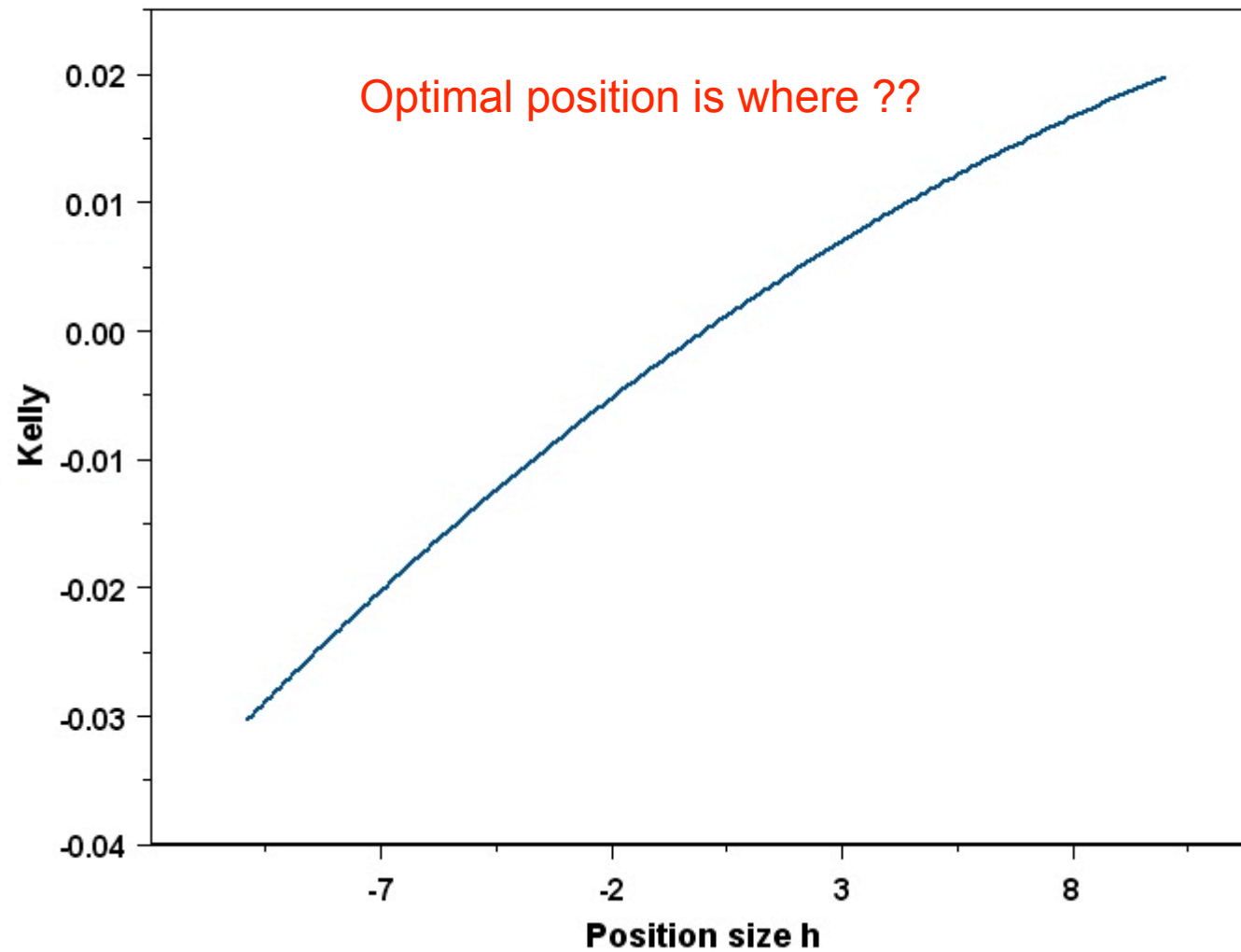
Not good –
any slightly positive expected return implies an extremely large position because there is no tail risk

Tsallis, $q = 1.5$

Good –
large position sizes are penalized by the tail risk

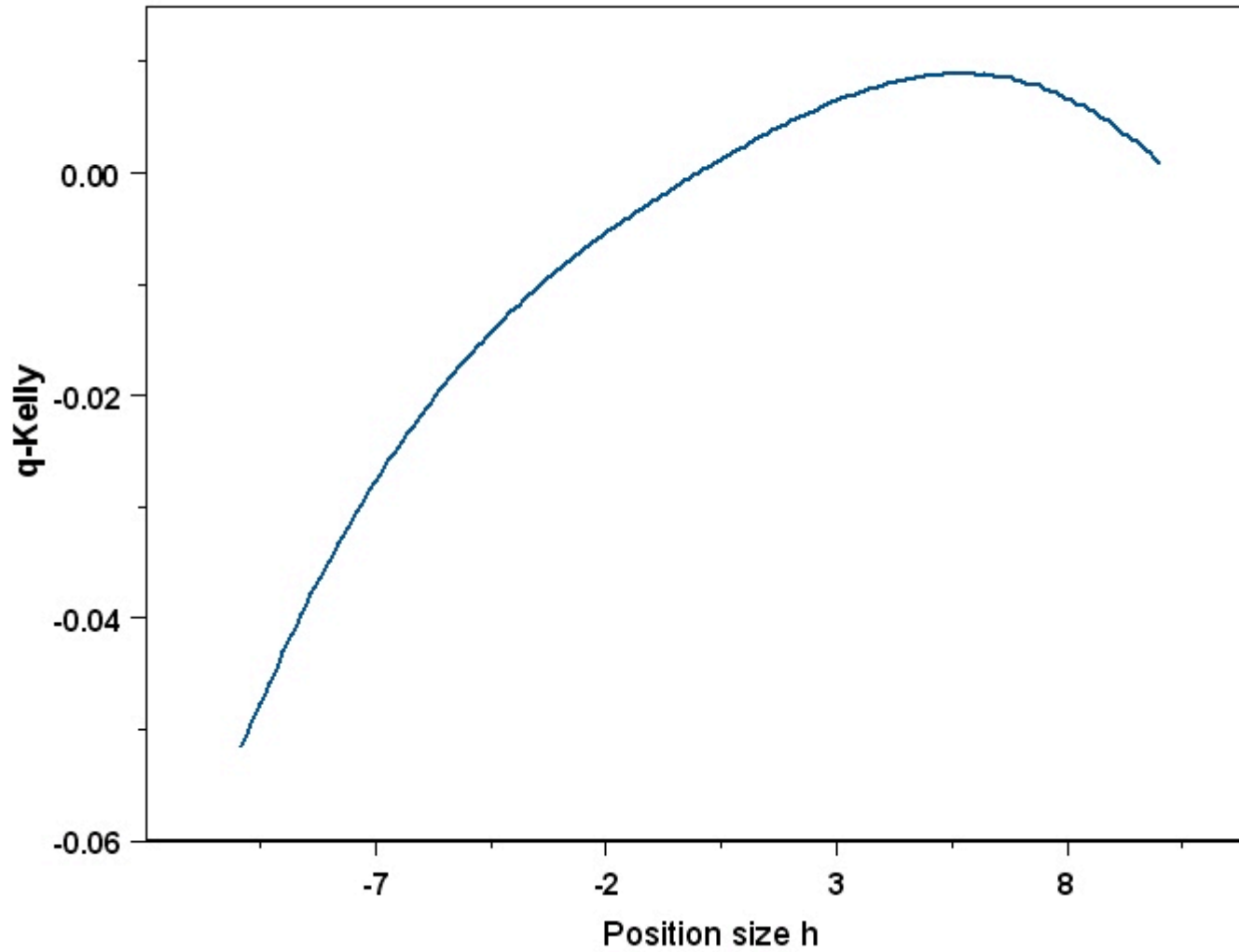
Example: Daily expected return $\mu = 25$ bp and $\sigma = 1$ %

Calculating Optimal Holdings with $q = 1$ (Gaussian)



Example: Daily expected return $\mu = 25$ bp and $\sigma = 1\%$

Calculating Optimal Holdings with $q = 1.5$



These portfolios might be optimal, but some investors might not like the high leverage

- i) Might not be log-utility maximizers
- ii) Might be irrational

- One more ingredient:

- Prospect Theory

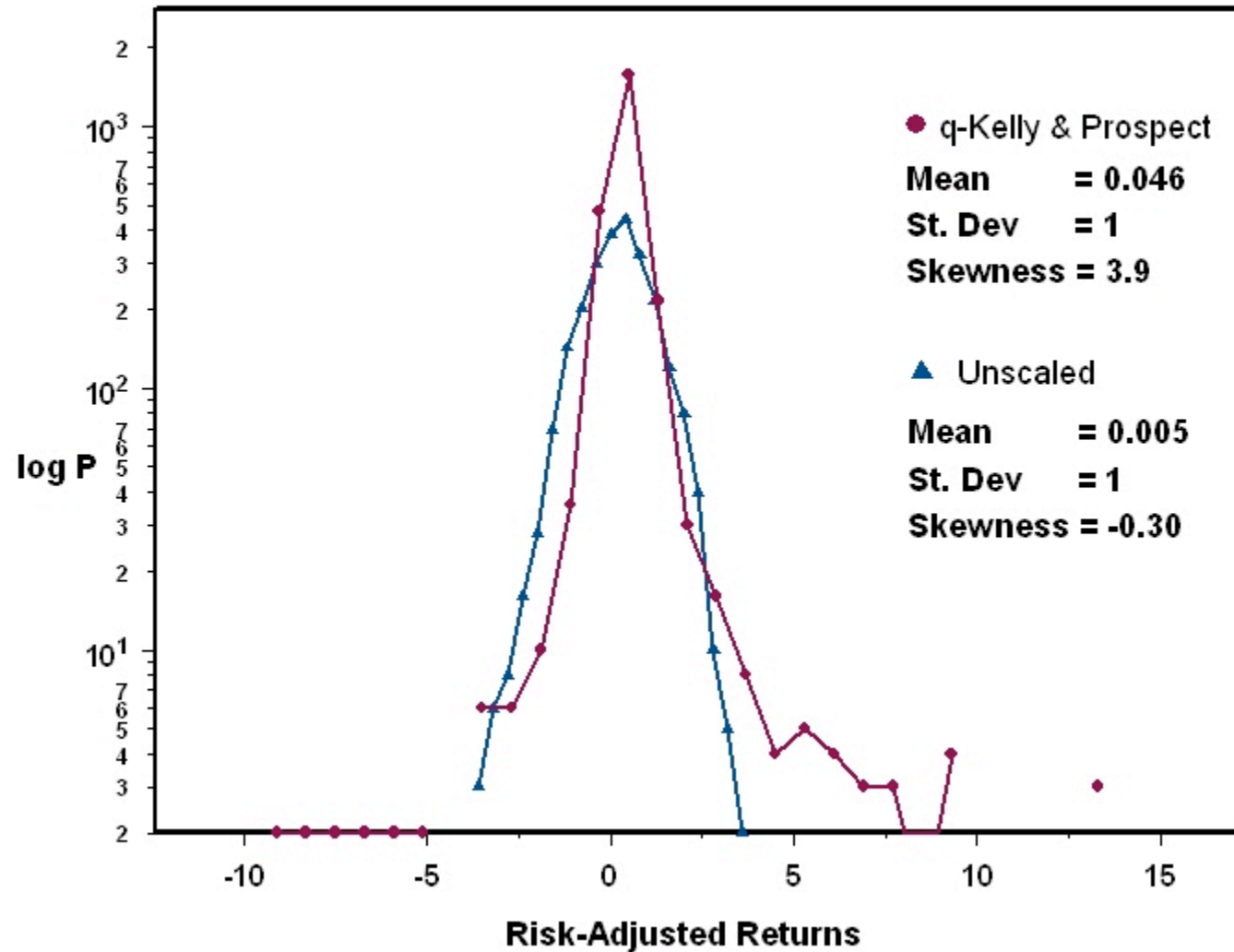
(Tversky and Kahneman, Nobel Prize 2002)

$$\left\langle \log(1 + hx) \right\rangle_{P(x|\mu, \sigma)^a}$$
$$a \leq 1$$

Gives even more weight to the tails – incorporates subjective investor fear, not just actual probability of losses

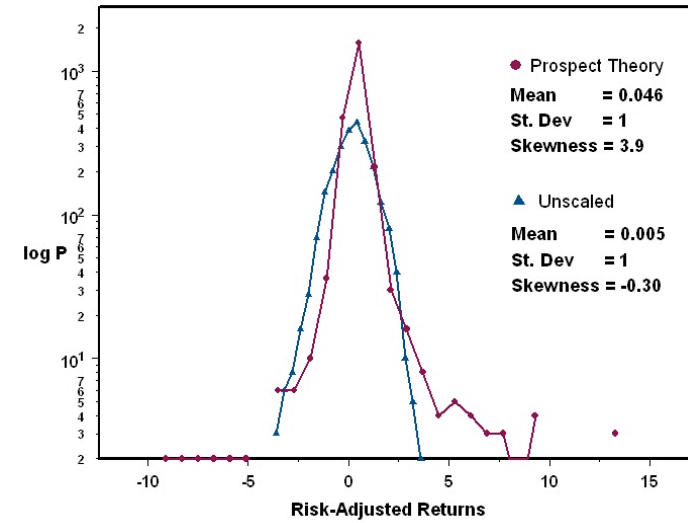
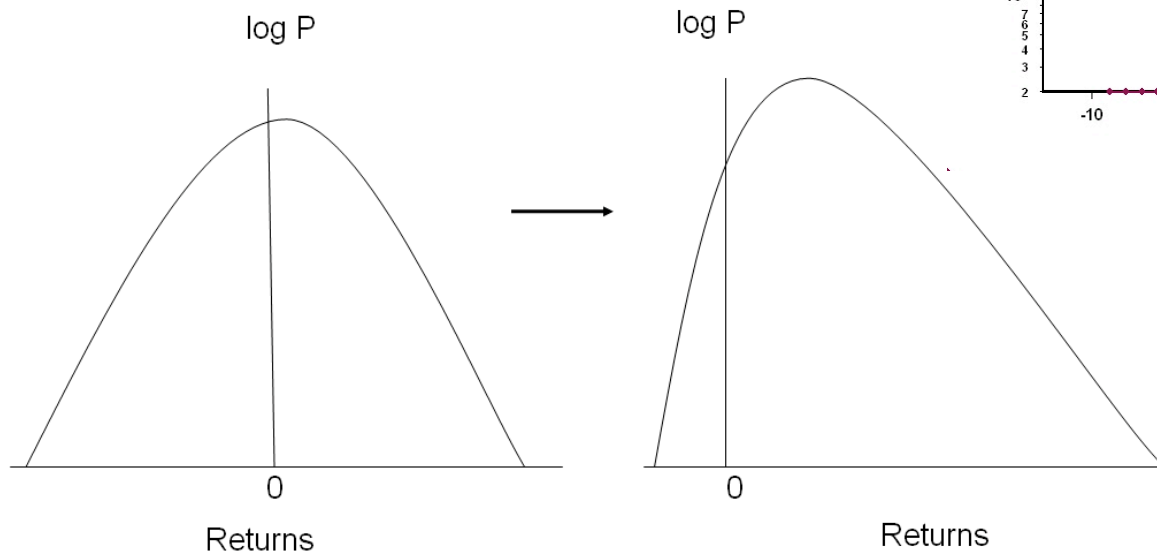
Results using q-Kelly & Prospect Theory $q=1.5, a = 0.8$:

A real trading strategy: returns with and without scaling



Same predictive signal but better risk control \rightarrow superior returns

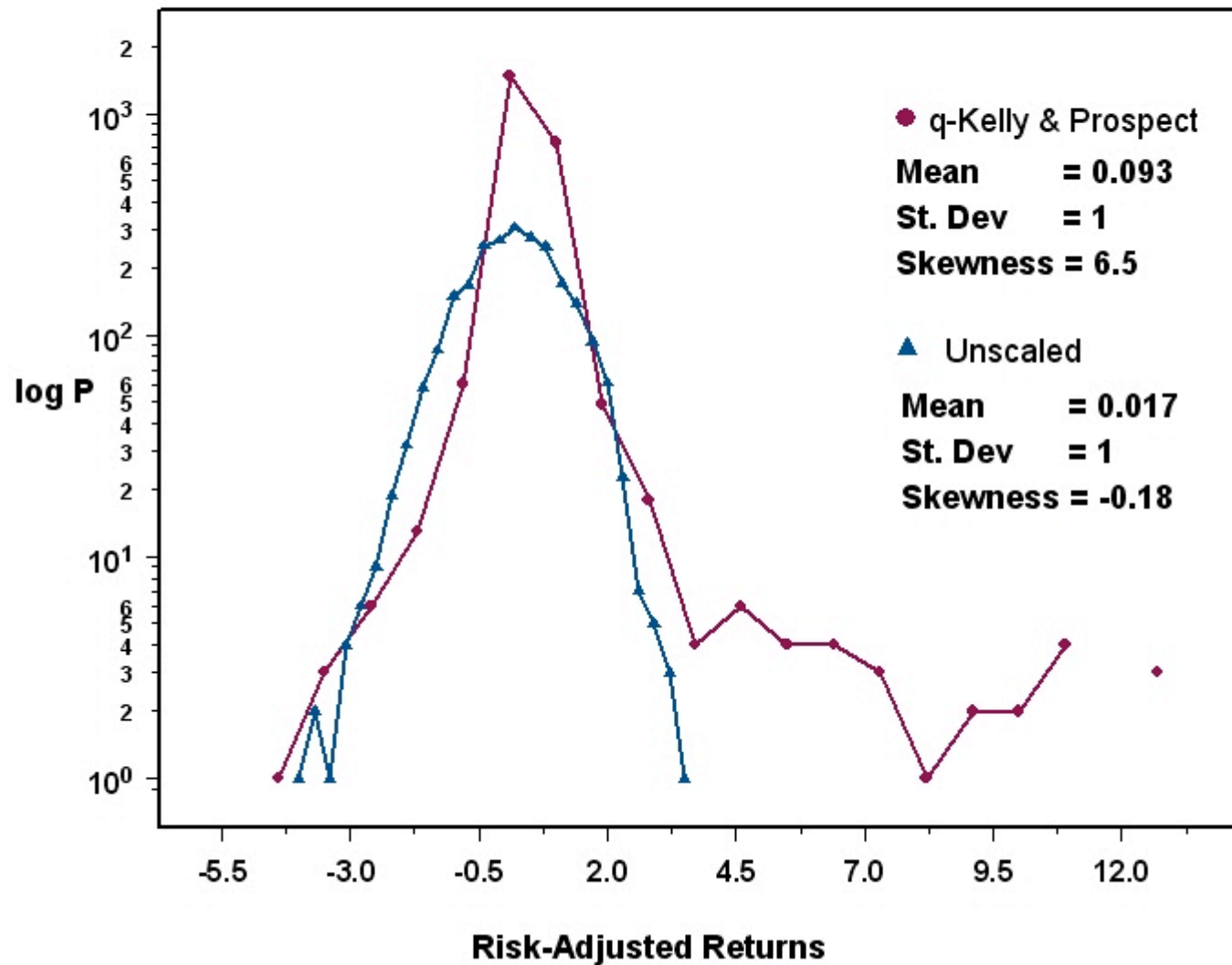
Remember our cartoon!



Ideally: A trading strategy transforms underlying asset return distribution favorably

Results using q-Kelly & Prospect Theory $q=1.5, a = 0.8$:

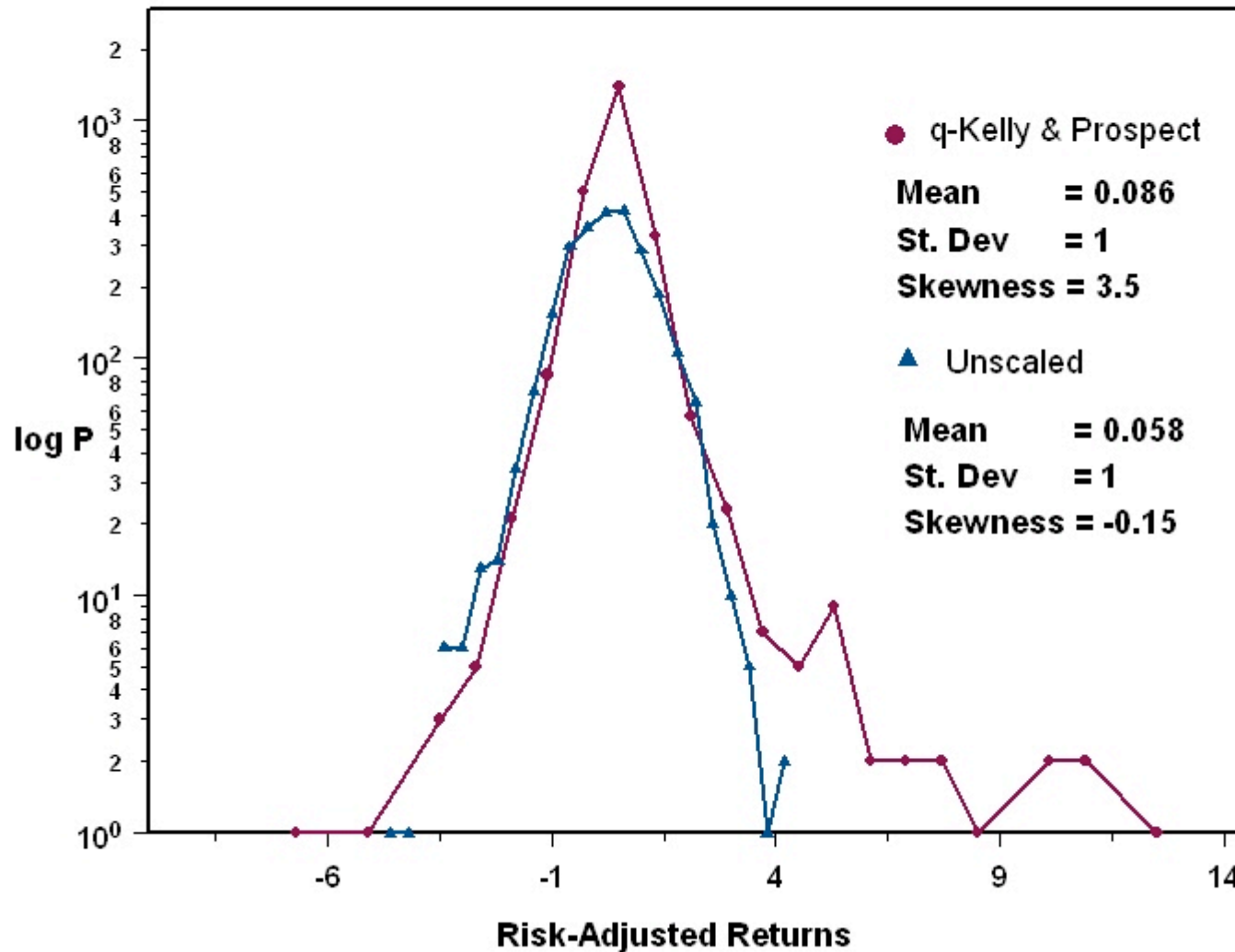
Another real trading strategy: returns with and without scaling



- Multi-strategy case:

Results using q-Kelly & Prospect Theory $q=1.5, a = 0.8$:

Applied to a multi-strategy portfolio of real trading strategies



- Multi-strategy case:
 - Combined strategies in a naive approximation
 - Used q-Kelly & Prospect Theory to get leverage rule for whole portfolio

Work still to be done:

- Use q-Kelly & Prospect Theory directly on the multivariate distribution
- Incorporate asymmetry between profit seeking and loss aversion.

Conclusions

- Hedge fund monthly returns distributed according to Tsallis distribution with $q = 1.4$
- This is quite stable across strategy types
- Using $q=1.4$, more robust VaR numbers can be calculated
- By taking tail risk into account, optimal position sizes can be found that – at least for the strategies studied here – produce more desirable return distributions