

ASSET ALLOCATION:
FALLACIES, CHALLENGES, AND SOLUTIONS

WILLIAM KINLAW

MARK KRITZMAN

DAVID TURKINGTON

THE IMPORTANCE OF ASSET ALLOCATION

Fallacy: Asset allocation determines more than 90 percent of performance

Fallacy: Time diversifies risk

Fallacy: Optimized portfolios are hypersensitive to input errors

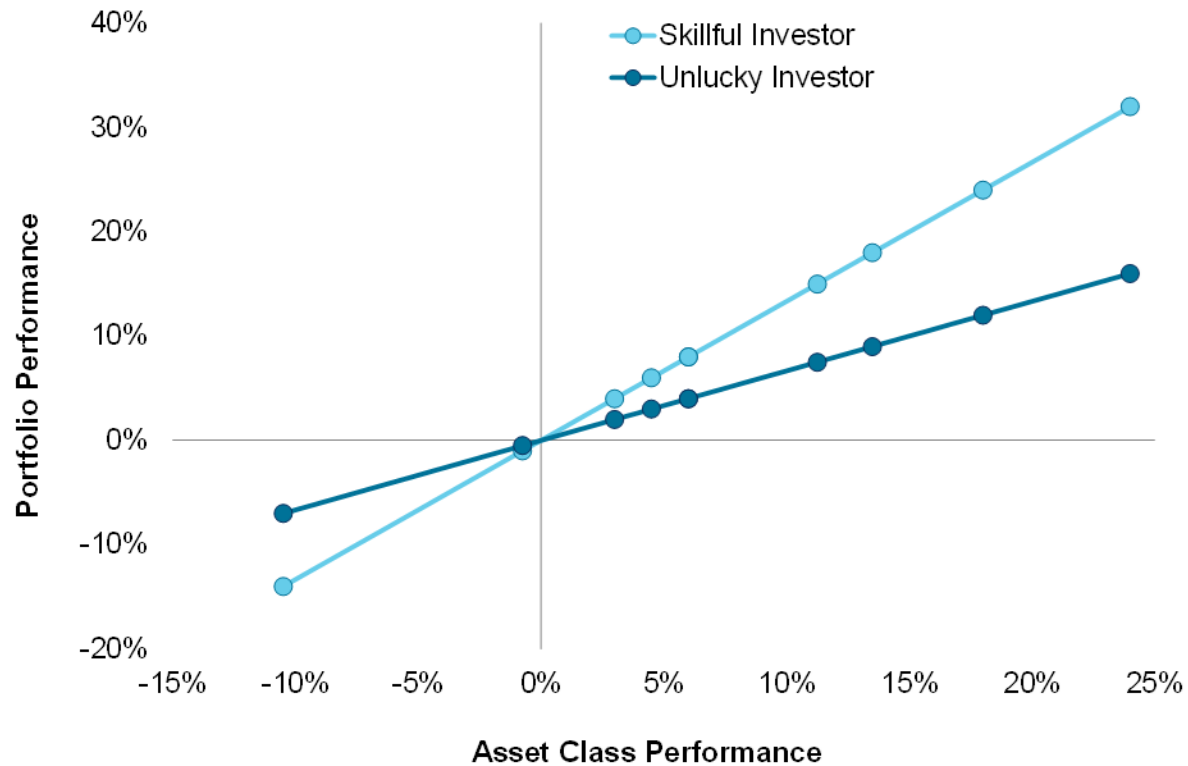
Fallacy: Factors offer superior diversification and noise reduction

THE IMPORTANCE OF ASSET ALLOCATION

Illustration of BHB Methodology

Period	Stock A	Stock B	Stock Index	Bond A	Bond B	Bond Index	Skillful Manager	Unlucky Manager
1	15.0%	7.5%	11.3%	15.0%	7.5%	11.3%	15.0%	7.5%
2	8.0%	4.0%	6.0%	8.0%	4.0%	6.0%	8.0%	4.0%
3	-1.0%	-0.5%	-0.8%	-1.0%	-0.5%	-0.8%	-1.0%	-0.5%
4	-14.0%	-7.0%	-10.5%	-14.0%	-7.0%	-10.5%	-14.0%	-7.0%
5	4.0%	2.0%	3.0%	4.0%	2.0%	3.0%	4.0%	2.0%
6	32.0%	16.0%	24.0%	32.0%	16.0%	24.0%	32.0%	16.0%
7	18.0%	9.0%	13.5%	18.0%	9.0%	13.5%	18.0%	9.0%
8	6.0%	3.0%	4.5%	6.0%	3.0%	4.5%	6.0%	3.0%
9	24.0%	12.0%	18.0%	24.0%	12.0%	18.0%	24.0%	12.0%
10	8.0%	4.0%	6.0%	8.0%	4.0%	6.0%	8.0%	4.0%
Average	10.0%	5.0%	7.5%	10.0%	5.0%	7.5%	10.0%	5.0%

THE IMPORTANCE OF ASSET ALLOCATION



TIME DIVERSIFICATION

Fallacy: **Asset allocation determines more than 90 percent of performance**

Fallacy: **Time diversifies risk**

Fallacy: **Optimized portfolios are hypersensitive to input errors**

Fallacy: **Factors offer superior diversification and noise reduction**

TIME DIVERSIFICATION

It is widely assumed that investing over long horizons is less risky than investing over short horizons, because the likelihood of loss is lower over long horizons.

Time, Volatility, and Probability of Loss

Expected continuous return: 10%

Continuous standard deviation: 20%

Investment Horizon	Annualized Continuous Standard Deviation	Probability of Loss (<0%) on Average over Horizon
1 Year	20.0%	30.9%
5 Years	8.9%	13.2%
10 Years	6.3%	5.7%
20 Years	4.5%	1.3%

TIME DIVERSIFICATION

Paul A. Samuelson showed that time does not diversify risk, because though the probability of loss decreases with time, the magnitude of potential losses increases with time.

Expected utility accounts for both the likelihood and magnitude of changes in wealth.

A certainty equivalent is the certain amount that conveys the same expected utility as a risky gamble.

$$\ln(\$100) = 4.6052$$

$$50\% \times \ln(\$100 \times 1.3333) + 50\% \times \ln(\$100 \times 0.75) = 4.6052$$

TIME DIVERSIFICATION

Expected Wealth and Expected Utility

	Initial Wealth	1st Period Distribution	2nd Period Distribution	3rd Period Distribution
			177.78 x .25	237.04 x .125
		133.33 x .50		133.33 x .125
			100.00 x .25	133.33 x .125
	100.00			75.00 x .125
			100.00 x .25	133.33 x .125
		75.00 x .50		75.00 x .125
			56.25 x .25	75.00 x .125
				42.19 x .125
Expected wealth	100.00	104.17	108.51	113.03
Expected utility	4.6052	4.6052	4.6052	4.6052

TIME DIVERSIFICATION

It is also true that the probability of loss within an investment horizon never decreases with time.

$$Pr_W = N \left[\frac{\ln(1+L) - \mu T}{\sigma \sqrt{T}} \right] + N \left[\frac{\ln(1+L) + \mu T}{\sigma \sqrt{T}} \right] (1 + L)^{\frac{2\mu}{\sigma^2}}$$

Probability of a Within-Horizon Loss

Continuous Expected Return: 10%

Continuous Standard Deviation: 20%

Investment Horizon	Probability of -10%
0.25 Years	22.1%
1 Year	44.1%
5 Years	56.7%
10 Years	58.4%
20 Years	59.0%
100 Years	59.1%

TIME DIVERSIFICATION

Finally, the cost of a protective put option increases with time to expiration. Therefore, because it costs more to insure against losses over longer periods than shorter periods, it follows that risk does not diminish with time.

Risky asset	100
Risk-free rate	3%
Volatility	20%
Strike Price	95

Time to Expiration	Price of Put Option
0.25	1.67
1	4.39
5	8.61
10	9.49

ERROR MAXIMIZATION

Fallacy: Asset allocation determines more than 90 percent of performance

Fallacy: Time diversifies risk

Fallacy: Optimized portfolios are hypersensitive to input errors

Fallacy: Factors offer superior diversification and noise reduction

ERROR MAXIMIZATION

If assets are close substitutes

<i>Expected returns:</i>	7.8%	7.6%	7.3%
<i>Standard deviations:</i>	25.3%	25.0%	21.5%
<i>Correlations:</i>	0.75	0.66	0.60

	Correct Weights	Incorrect Weights*	Mis-allocation
France	25.5%	−5.7%	−31.2%
Germany	23.8%	44.9%	21.1%
United Kingdom	50.7%	60.8%	10.1%
Total			62.4%

Probability of 10% or greater loss Difference

End of 1 year	19.2%	20.1%	0.9%
Within 1 year	47.6%	48.8%	1.2%

If assets are not close substitutes

<i>Expected returns:</i>	8.8%	4.1%	6.2%
<i>Standard deviations:</i>	16.6%	5.7%	20.6%
<i>Correlations:</i>	0.10	0.16	−0.07

	Correct Weights	Incorrect Weights*	Mis-allocation
U.S. Equities	66.7%	55.0%	−11.7%
U.S. Treasuries	19.8%	27.0%	7.2%
Commodities	13.5%	18.0%	4.5%
Total			23.5%

Probability of 10% or greater loss Difference

End of 1 year	6.1%	4.4%	−1.7%
Within 1 year	17.7%	12.9%	−4.9%

In both examples, we introduce expected return errors as follows: we increase the expected returns of the first asset and the third asset by 1%, and we decrease the expected return of the second asset by 1%.

*Source: A Practitioner's Guide to Asset Allocation, Wiley 2017
Analysis is based on data spanning Jan 1976 through Dec 2015.*

FACTORS

Fallacy: **Asset allocation determines more than 90 percent of performance**

Fallacy: **Time diversifies risk**

Fallacy: **Optimized portfolios are hypersensitive to input errors**

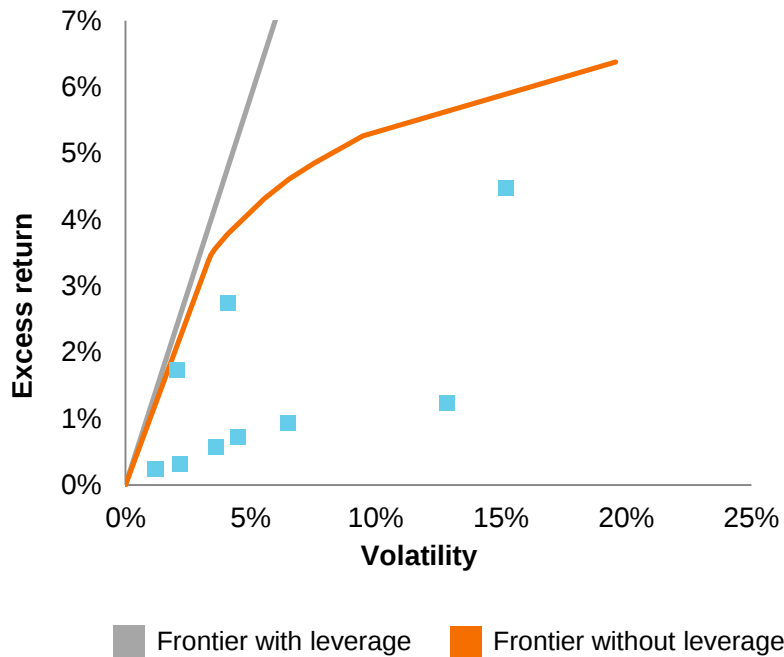
Fallacy: Factors offer superior diversification and noise reduction

FACTORS

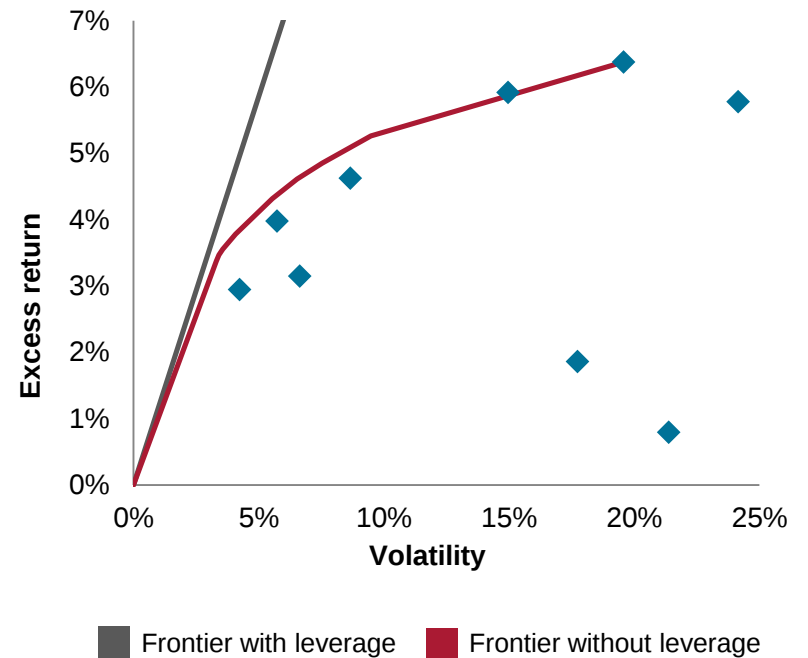
- Some investors believe that factors offer greater potential for diversification than asset classes because they appear less correlated than asset classes.
- Factors appear less correlated only because the portfolio of assets designed to mimic them includes short positions.
- Given the same constraints and the same investible universe, it is mathematically impossible to regroup assets into factors and produce a better efficient frontier.

FACTORS

Principal components (all factors uncorrelated)



Asset classes (correlations range from -0.16 to 0.82)



Notes: This analysis incorporates the following asset classes: U.S. large cap, U.S. small cap, EAFE equities, emerging equities, global sovereigns, U.S. government bonds, U.S. corporate bonds, commodities, and hedge funds. It is based on monthly returns over the period Jan 1990 through Dec 2013. Excess returns represent the return over the risk-free rate. All data obtained from DataStream.

FACTORS

- Some investors believe that consolidating a large group of securities into a few factors reduces noise more effectively than consolidating them into a few asset classes.
- Consolidation reduces noise around means but no more so by using factors than by using asset classes.
- Consolidation does not reduce noise around covariances.

CONSTRAINTS

Challenge: Identify acceptable portfolios without imposing constraints

Challenge: Determine the optimal exposure to illiquid assets

Challenge: Construct optimal portfolios in the presence of estimation error

Challenge: Construct portfolios to accommodate shifting risk regimes

CONSTRAINTS

Mean-variance optimization:

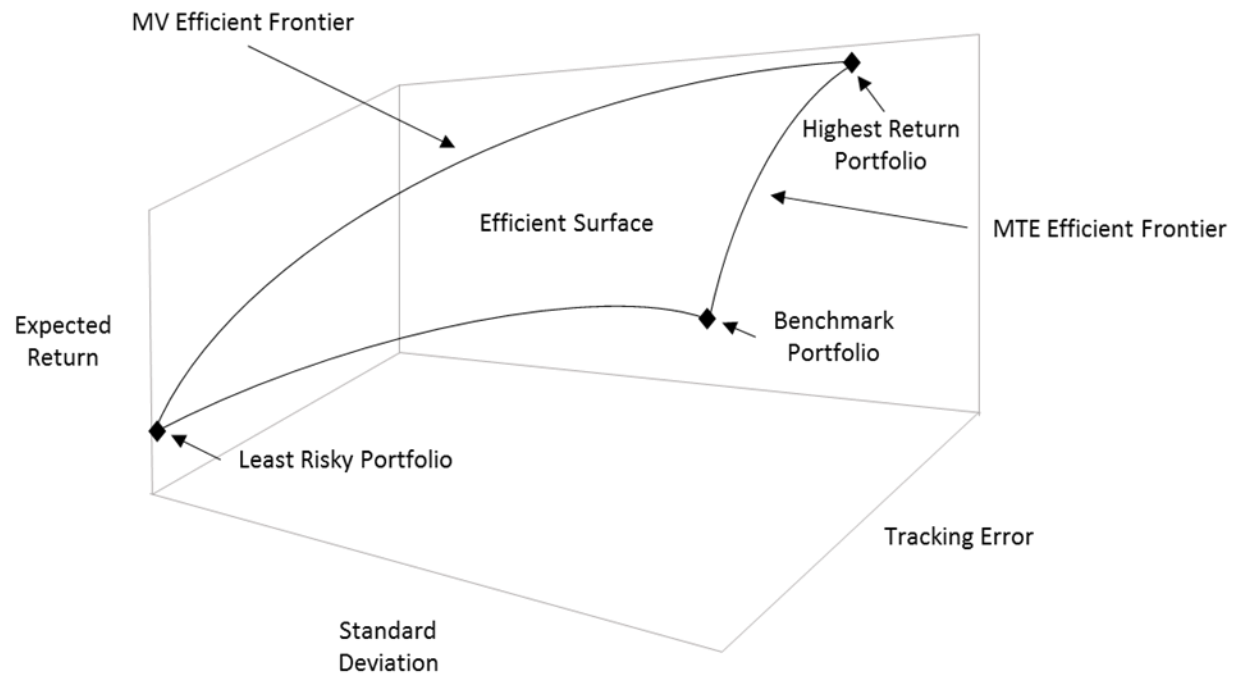
$$E(U) = \mu_p - \lambda_{RA}\sigma_p^2$$

Mean-variance-tracking error optimization:

$$E(U) = \mu_p - \lambda_{RA}\sigma_p^2 - \lambda_{TEA}\xi_p^2$$

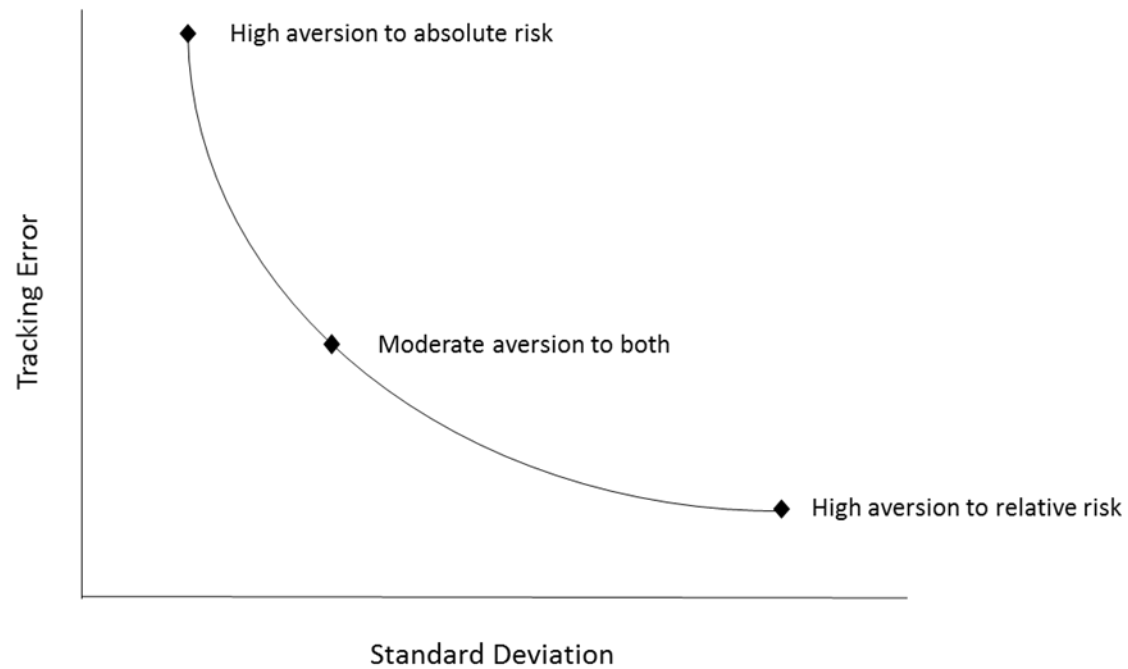
CONSTRAINTS

Efficient Surface



CONSTRAINTS

Iso-Expected Return Curve



ILLIQUIDITY

Challenge: **Identify acceptable portfolios without imposing constraints**

Challenge: **Determine the optimal exposure to illiquid assets**

Challenge: Construct optimal portfolios in the presence of estimation error

Challenge: **Construct portfolios to accommodate shifting risk regimes**

ILLIQUIDITY

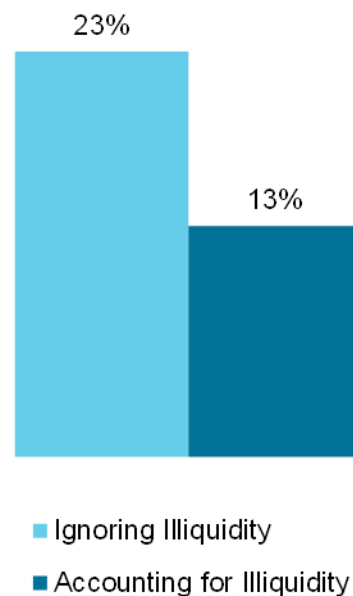
Shadow assets and liabilities

The value of liquidity and cost of illiquidity will differ for each investor. This illustration offers plausible estimates.

	Return	Volatility
Shadow assets (attached to liquid assets)		
Tactical asset allocation	40	80
Shadow liabilities (attached to illiquid assets)		
Sub-optimality: weight drift	16	0
Sub-optimality: cash demands	18	0
Borrowing: cash demands	17	10

Optimal allocation to real estate

The optimal allocation decreases when we account for illiquidity.



ESTIMATION ERROR

Challenge: **Identify acceptable portfolios without imposing constraints**

Challenge: **Determine the optimal exposure to illiquid assets**

Challenge: **Construct optimal portfolios in the presence of estimation error**

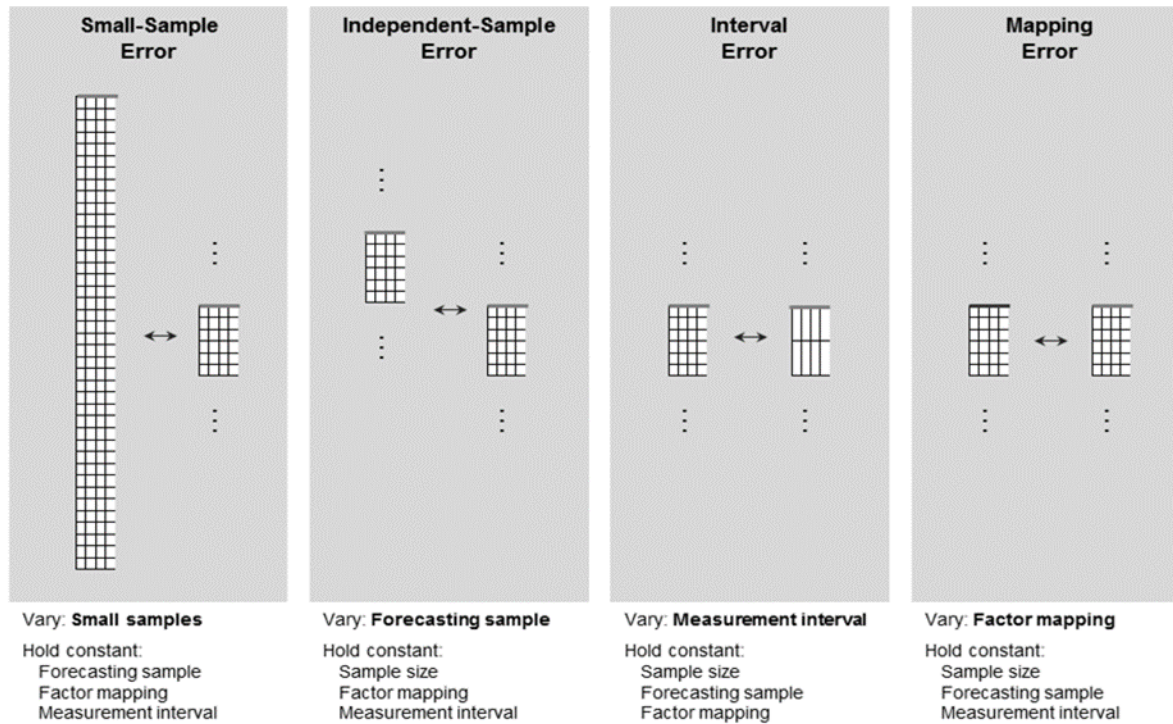
Challenge: **Construct portfolios to accommodate shifting risk regimes**

ESTIMATION ERROR

- When investors estimate asset class covariances from historical returns they face three types of estimation error: small-sample error, independent-sample error, and interval error.
- Small-sample error arises because the investor's investment horizon is typically shorter than the historical sample from which covariances are estimated.
- Independent-sample error arises because the investor's investment horizon is independent of history.
- Interval error arises because investors estimate covariances from higher frequency returns than the return frequency they care about.
- Common approaches for controlling estimation error, such as Bayesian shrinkage and resampling, make portfolios less sensitive to estimation error.
- A new approach, called stability-adjusted optimization delivers portfolios that rely more on relatively stable covariances and less on relatively unstable covariances.

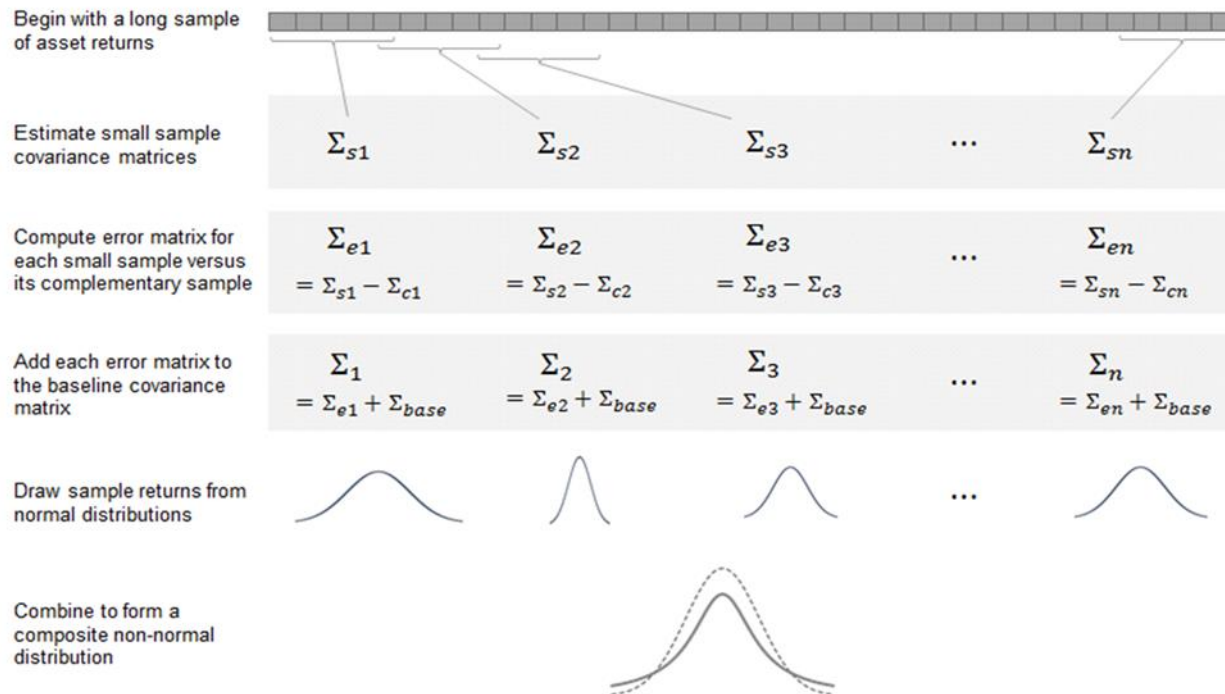
ESTIMATION ERROR

Components of Estimation Error



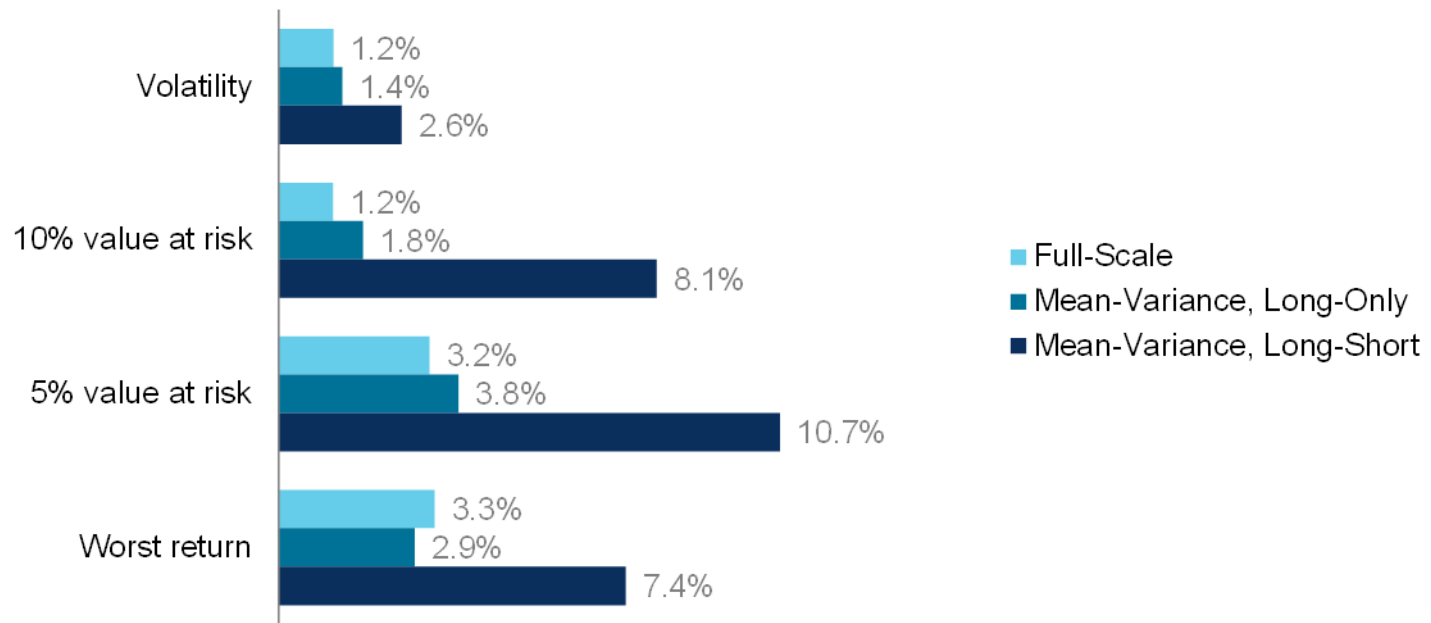
ESTIMATION ERROR

Constructing the Stability-Adjusted Return Distribution



ESTIMATION ERROR

Improvement in 10% Worst Outcomes:
Stability Adjustment versus Error Blind



REGIME SHIFTS

Challenge: **Identify acceptable portfolios without imposing constraints**

Challenge: **Determine the optimal exposure to illiquid assets**

Challenge: **Construct optimal portfolios in the presence of estimation error**

Challenge: Construct portfolios to accommodate shifting risk regimes

REGIME SHIFTS

$$Turbulence_t = \frac{1}{N} (\mathbf{x}_t - \boldsymbol{\mu})' \boldsymbol{\Sigma}^{-1} (\mathbf{x}_t - \boldsymbol{\mu})$$

$\mathbf{x}_t$ is a vector of monthly returns across asset classes.

$\boldsymbol{\mu}$ is a vector of average returns for each asset class over the full 40-year sample.

$\boldsymbol{\Sigma}^{-1}$ is the inverse of the covariance matrix computed from the 40-year sample.

REGIME SHIFTS

Hidden Markov Model Fit and Conditional Asset Class Performance

Hidden Markov Model Fit: Turbulence	Calm	Moderate	Turbulent
Regime Persistence	92%	75%	67%
Turbulence Average	0.7	1.1	1.7
Turbulence Standard Deviation	0.2	0.3	0.6

Average Annual Asset Return	Calm	Moderate	Turbulent
U.S. Equities	15.0%	13.6%	-27.7%
Foreign Developed Market Equities	15.3%	5.7%	-12.0%
Emerging Market Equities	17.2%	21.7%	-26.0%
Treasury Bonds	5.9%	9.6%	12.3%
U.S. Corporate Bonds	7.5%	10.2%	4.2%
Commodities	7.8%	7.8%	-17.1%
Cash Equivalents	3.9%	5.9%	7.4%

Asset Standard Deviations	Calm	Moderate	Turbulent
U.S. Equities	12.6%	20.2%	19.9%
Foreign Developed Market Equities	14.7%	19.6%	31.0%
Emerging Market Equities	21.3%	30.5%	32.5%
Treasury Bonds	4.2%	6.4%	12.1%
U.S. Corporate Bonds	5.1%	7.8%	16.6%
Commodities	18.1%	21.3%	30.3%
Cash Equivalents	0.8%	1.1%	1.7%

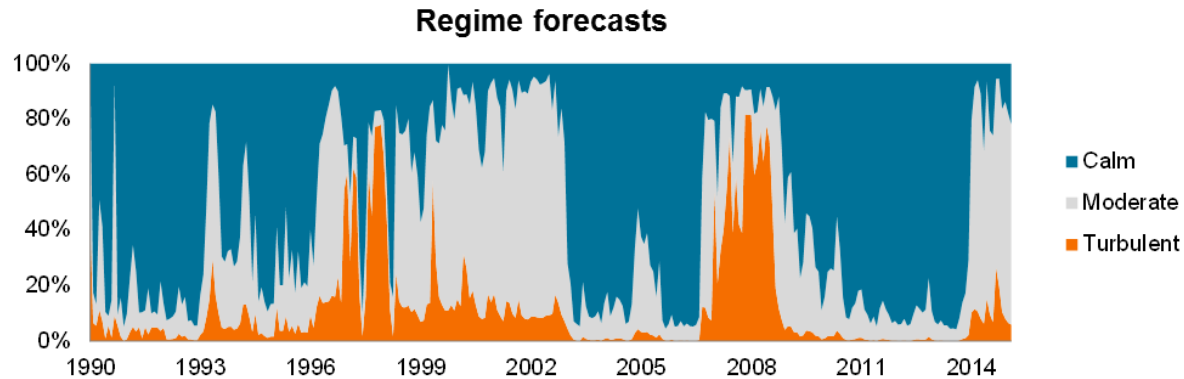
REGIME SHIFTS

Next Period Probability of Each Regime

$$\begin{bmatrix} P(\varphi_{t+1} = A) \\ P(\varphi_{t+1} = B) \\ P(\varphi_{t+1} = C) \end{bmatrix} = \begin{bmatrix} P(\varphi_{t+1} = A|\varphi_t = A) & P(\varphi_{t+1} = A|\varphi_t = B) & P(\varphi_{t+1} = A|\varphi_t = C) \\ P(\varphi_{t+1} = B|\varphi_t = A) & P(\varphi_{t+1} = B|\varphi_t = B) & P(\varphi_{t+1} = B|\varphi_t = C) \\ P(\varphi_{t+1} = C|\varphi_t = A) & P(\varphi_{t+1} = C|\varphi_t = B) & P(\varphi_{t+1} = C|\varphi_t = C) \end{bmatrix} \begin{bmatrix} P(\varphi_t = A) \\ P(\varphi_t = B) \\ P(\varphi_t = C) \end{bmatrix}$$

REGIME SHIFTS

Estimated probability of each regime occurring next month, calibrated on prior data at each point in time.



Cumulative returns of static portfolios, and tactical strategy that allocates proportional to regime forecasts.

