STATE STREET GLOBAL MARKETS. Investment Research and Trading

Can we trust portfolio optimization when building a globally diversified portfolio?

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Portfolio Optimization and Global Diversification

- The Canadian equity market represents only 4% of the world market capitalization. When using equilibrium return assumptions, most portfolio optimization models suggest only a small allocation to Canadian equities, even in the presence of Canadian liabilities.
- Can we trust portfolio optimization when building globally diversified portfolios? Recently we have seen a growing scepticism of portfolio optimization techniques. For example, previous research shows that equally weighted portfolios ("1/N") outperform optimized portfolios.
- With naïve inputs we demonstrate that optimized portfolios usually outperform equally weighted portfolios, and therefore the home bias remains a puzzle.

Is Portfolio Optimization Dead?

- Bernartzi and Thaler (2001) demonstrate that equally weighted diversification ("1/N" diversification) is ingrained in human behavior.
- Previous research shows that 1/N portfolios outperform optimized portfolios out of sample. See: Jobson and Korkie (1981), DeMiguel, Garlappi, and Uppal (2007), and Duchin and Levy (2009).
- DeMiguel, Galarppi, and Uppal's study is particularly convincing because the authors evaluate fourteen models on seven empirical datasets. They find that none of the fourteen models consistently outperforms 1/N.

Better Behaved Portfolios?

- In practice, most investors employ constraints when they optimize their portfolio.
- Jorion (1986, 1991) introduces the Bayes-Stein approach, which compresses expected returns towards the minimum-variance portfolio.
- Michaud (1989) discusses error maximization and Michaud (1998) introduces re-sampling as a method to reduce estimation error.
- Black and Litterman (1992) combine views with equilibrium expected returns to reduce extreme allocations.

Better Behaved Portfolios?

- Chow (1995) achieves the same objective by augmenting the mean-variance objective function with a benchmark tracking error term, which yields better outcomes than imposing ad-hoc constraints.

- Chevrier (2009) uses economic theory – together with advances in Bayesian estimation – to build optimal portfolios. The resulting portfolios are better behaved than, and outperform, 1/N.

Questioning Conventional Wisdom

- Fisher and Statman (1997) argue that extreme allocations are not due to estimation errors. Optimal portfolios may include extreme positions even when the true parameters are used.

- Kritzman (1998) explains that no-one likes to be wrong and alone.

- Scherer (2002) demonstrates that resampling converges to the mean-variance solution when short sales are allowed.

- Kritzman (2003) dismisses the adage “garbage in – garbage out” and Kritzman (2006) demonstrates that high sensitivity to inputs occurs when assets have similar expected returns and risk.

Our Experiment

- We perform backtests to compare the out-of-sample performance of
  - The 1/N portfolio
  - The market portfolio
  - Optimized portfolios

- However, instead of rolling historical returns, we use simple models of expected returns that do not require forecasting skill.

- Our study covers 13 datasets comprised of 1,028 data series representing 4.4 million data points. We construct over 50,000 optimized portfolios and evaluate their out-of-sample performance.

Asset-Liability Management

Asset Class	Source	Start	End
Domestic Equity	S&P 500	Feb 1973	Dec 2008
Foreign Equity	MSCI EAFE	Feb 1973	Dec 2008
Domestic Government	Barclays US Govt	Feb 1973	Dec 2008
Domestic Corporate	Barclays US Corp	Feb 1973	Dec 2008
REITs	FTSE/NAREIT	Feb 1973	Dec 2008
Commodities	S&P GSCI	Feb 1973	Dec 2008
Cash	Ken French (1m T-bill)	Feb 1973	Dec 2008
Liabilities (Remeaned)	Barclays US Govt Long	Feb 1973	Dec 2008

Betas

Asset Class	Source	Start	End
10 Industries	CRSP/Ken French	Jul 1926	Dec 2008
30 Industries	CRSP/Ken French	Jul 1926	Dec 2008
10 Size Deciles	CRSP/Ken French	Jul 1926	Dec 2008
10 Book-to-market deciles	CRSP/Ken French	Jul 1926	Dec 2008
10 Dividend yield deciles	CRSP/Ken French	Jul 1927	Dec 2008
10 Momentum deciles	CRSP/Ken French	Jan 1927	Dec 2008
10 Long-term reversal deciles	CRSP/Ken French	Jan 1931	Dec 2008
10 Short-term reversal deciles	CRSP/Ken French	Feb 1926	Dec 2008

Alphas

Asset Class	Source	Start	End
Security selection (500 stocks)	S&P 500 Constituents	Dec 1998	Dec 2008
21 Commodities	S&P/GSCI	Jan 1971	Dec 2008
14 Hedge fund styles	HFRI	Jan 1996	Dec 2008
15 Asset managers	Yahoo	May 1987	Dec 2008

Constituents: Commodities

Wheat	Cotton	Platinum
Live Cattle	Live Hogs	Crude Oil
Corn	Copper	Cocoa
Soybeans	Gold	Aluminium
Grains	Coffee	Zinc
Silver	Petroleum	Nickel
Sugar	Heating Oil	Natural Gas

Constituents: Hedge Fund Styles

Equity Market Neutral	Private Issues – Reg D	Corporates
Quant Directional	Merger Arbitrage	Asset-Backed
Short Bias	Systematic Diversified	Yield Alternatives
Tech - Healthcare	Multi-Strategy	
Energy	Convertible Arbitrage	

Constituents: Asset Managers

American Funds Fund. Investors	Fidelity Growth Company	Fidelity Equity-Income
Davis NY Venture A	American Funds Invt Co of Amer A	Columbia Acorn Z
Vanguard	American Funds Was. Mutual A	T. Rowe Price Mid-Cap Growth
American Funds Growth	Dodge & Cox Stock	Fidelity Value
Fidelity Contrafund	Vanguard Windsor II	Perkins Mid Cap Value Investor

Fund Screener:
- Any U.S. Stock Funds
- Manager Tenure: Longer than 10 Years
- Net Assets: >$5 billion
- Remove redundant funds

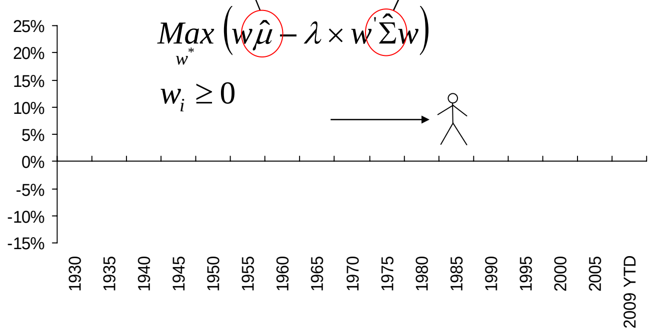
Backtesting

Expected Returns: Minimum Variance, Constant Risk Premium, and All-Data Risk Premium.

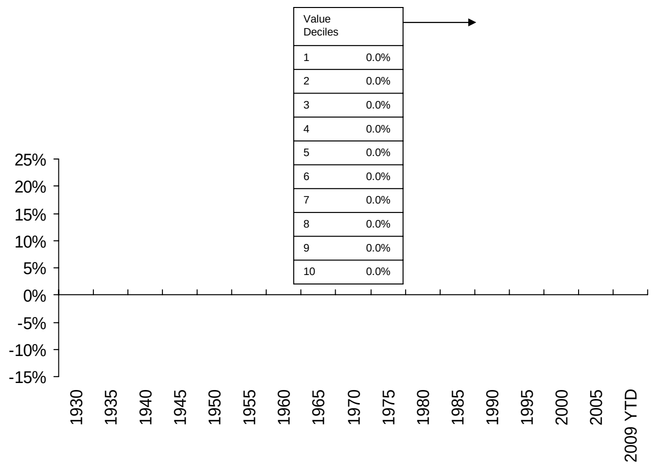
Covariance Matrix: Equally-Weighted (5,10, and 20 Years, All-Data, and 3-Year Daily for Security Selection).

$$\underset{w^*}{Max}\left(w\hat{\mu} - \lambda \times w'\hat{\Sigma}w\right)$$

$$w_i \geq 0$$

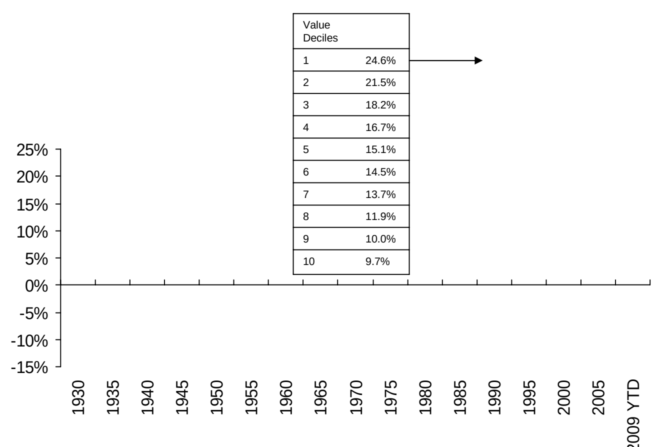


Expected Returns: Minimum Variance



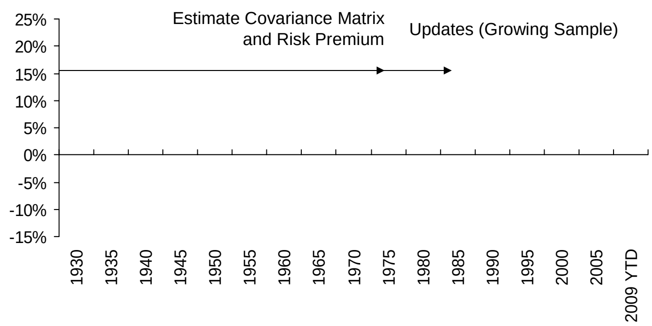
Value Deciles	
1	0.0%
2	0.0%
3	0.0%
4	0.0%
5	0.0%
6	0.0%
7	0.0%
8	0.0%
9	0.0%
10	0.0%

Constant Risk Premium



Value Deciles	
1	24.6%
2	21.5%
3	18.2%
4	16.7%
5	15.1%
6	14.5%
7	13.7%
8	11.9%
9	10.0%
10	9.7%

The All-Data Approach



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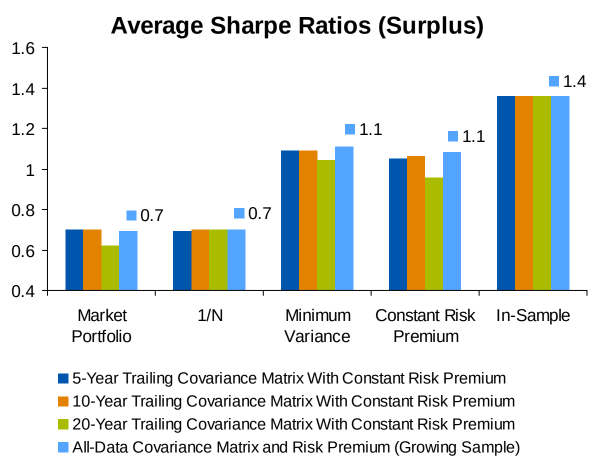
Asset-Liability Management



Assuming 40 bps round-trip transaction costs, the estimated impact of transaction costs on Sharpe ratios are: -0.02 for 1/N, -0.04 for Minimum Variance, and -0.05 for Constant Risk Premium.

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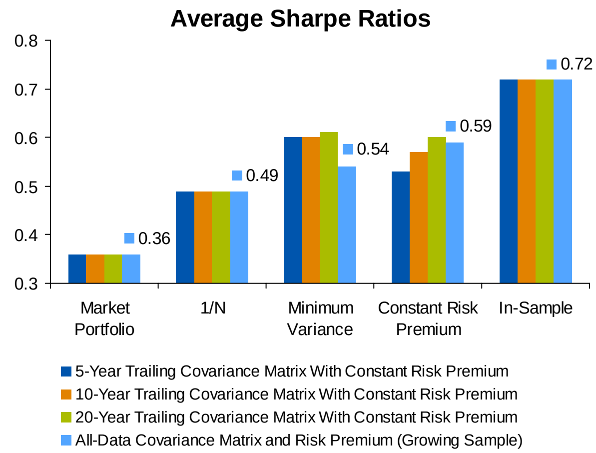
Betas



Assuming 40 bps round-trip transaction costs, the estimated impact of transaction costs on Sharpe ratios are: -0.002 for 1/N, -0.008 for Minimum Variance, and -0.009 for Constant Risk Premium.

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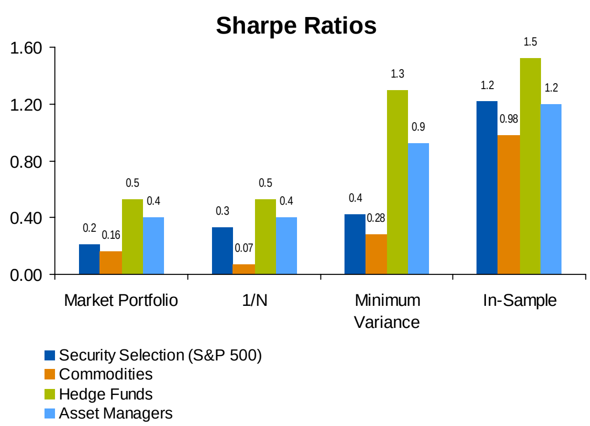
Alphas



Assuming 40 bps round-trip transaction costs, the estimated impact of transaction costs on Sharpe ratios for minimum variance are: -0.04 for security selection, -0.02 for commodities, -0.17 for hedge funds, and -0.06 for asset managers; for 1/N the estimated impact is -0.01 in all cases. Results are preliminary.

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Better Risk Estimates

- Risk parameters, such as standard deviation and correlation, estimated from full samples provide unreliable measures of the hedging and diversification properties of assets during turbulent markets (Chow, Jacquier, Kritzman, and Lowry, 1999).
- It is possible to use multivariate outliers to measure market turbulence.
- By measuring turbulence, we can
  - estimate risk parameters more reliably,
  - build portfolios that are more resilient to turbulent markets, and
  - build dynamic regime-switching models (Kritzman, Lowry, and Van Royen, 2001).

Higher Moments

- Mean-variance optimization assumes either that returns are normally distributed or quadratic utility is a good approximation of investor preferences.
- Full-scale optimization (Cremers, Kritzman, and Page, 2005, Adler and Kritzman, 2007, Chua, Kritzman, and Page, 2009), also called direct utility maximization (Sharpe, 2007) identifies the optimal portfolio given any set of return distributions and based on any description of investor preference.
- Full-scale optimization has been shown to outperform mean-variance optimization out-of-sample.

Full-Scale vs Mean-Variance Optimization

- Hedge fund returns are notoriously non-normal (see Alexiev 2004, Davies et al., 2003, Fung and Hsieh, 2000, Gregoriou and Gueyie, 2003, Kat and Lu, 2002, Lo, 2001, Lo 2005, and McFall, 2003).

- Using a sample of 32 hedge funds from 1994-2003 and four utility functions, Adler and Kritzman demonstrate that full-Scale optimization outperforms mean-variance optimization out-of-sample:

1994-1998	**Increase in Utility**	**Frequency of FS > M-V Utility**
Kinked at -1%	24%	67%
Kinked at -5%	316%	85%
S-shaped at 0%	2%	93%
S-shaped at 0.5%	4%	98%
1999-2003		
Kinked at -1%	6%	61%
Kinked at -5%	4%	56%
S-shaped at 0%	4%	78%
S-shaped at 0.5%	36%	91%

Conclusion

- DeMiguel, Garlappi, and Uppal (2007) claim that 1/N outperforms mean-variance optimization.

- Their results are highly dependent on the assumption that we can model expected returns using trailing 60-month and 120-month historical returns.

- Our contribution is not to build clever models of expected returns; we simply show that by removing our reliance on rolling mean returns, the value of optimization becomes evident.

- Quantitative and fundamental practitioners should focus on building models of expected returns that will combine with – and improve on – the risk-minimizing portfolio.