



**Asset
Management**

Quantitative Investment Strategies

August 2017

The model portfolio provided herein has certain limitations. These results are based on simulated or hypothetical performance results that have certain inherent limitations. Unlike the results shown in an actual performance record, these results do not represent actual trading. Also, because these trades have not actually been executed, these results may have under- or over-compensated for the impact, if any, of certain market factors, such as lack of liquidity. Simulated or hypothetical trading programs in general are also subject to the fact that they are designed with the benefit of hindsight. No representation is being made that any account will or is likely to achieve profits or losses similar to those being shown. Models do not represent the deduction of fees or commissions. This information is shown for illustrative purposes only and does not constitute a securities recommendation. This material is provided for educational purposes only and should not be construed as investment advice or an offer or solicitation to buy or sell securities.

Diversifying Managed Futures

We use a simple trend-following model to quantify the impact of asset diversification in Managed Futures. Using a large sample of over 80 assets, we show that the strategy's information ratio, when viewed as a function of the number of traded assets, continues to show meaningful improvement, even at the edge of our sample. Its other favorable process characteristics, including its low correlation with equities, are left intact. Moreover, the beneficial effects of this diversification are even greater when the marginal assets are sourced from different sectors. These findings strongly suggest that investors should seek trend-following managers who diversify their risk budgets across a large number of distinct assets and a variety of sectors.

I. Introduction

Although Managed Futures strategies vary in their selection of trading signals and assets, all share the common premise that price trends persist. Often implemented by commodity trading advisors ("CTAs"), trend-following strategies have recently attracted both significant assets and research attention, primarily due to their favorable performance and risk profiles over recent decades, including periods of challenged performance among traditional asset classes. In fact, assets under management (AUM) in such strategies now exceed \$348.1bn in 2017, according to BarclayHedge, up from \$37.9bn in 2000.

Early Managed Futures research tended to focus primarily on its desirable properties as an asset class. Edwards et al (1996) and Edwards et al (1999), for example, analyzed composite fund results and found significant evidence of both positive returns and low equity market correlation, two characteristics typically considered ideal for alternative investments. When blended with a traditional 60/40 portfolio, Managed Futures generally improved the composite Sharpe ratio and other performance metrics.

The increasing popularity of trend-following strategies has prompted deeper examinations focused on understanding what drives their signals and therefore excess returns. For example, Hurst et al (2013) show that a simple time series momentum model closely tracks aggregated Managed Futures indexes and explains a significant fraction of the associated alpha. Such analyses are useful not only because they help explain why Managed Futures perform well in relation to well-established behavioral finance theories, but also because the associated models provide insight into how a typical Managed Futures strategy might respond to various market events.

In this same vein, our paper seeks to understand in detail how the number and diversity of assets traded by a trend-following strategy impact performance. Key to our analysis is the use of over 80 tradable assets, a total that exceeds many other recent studies. We focus on these characteristics because they turn out to be critical determinants of the strategy's excess return, its information ratio, and its drawdown risk profile. For example, in our setting we estimate that on average, doubling the number of traded assets increases the strategy's information ratio by approximately 28% while reducing its drawdown by 7%. As important, its correlations to the primary assets, such as equities, remain quite low. We also show that the benefit of this "naïve" asset diversification is even greater when unrelated assets (i.e., those from different sectors and asset classes) are introduced into the model.

Our analysis provides several actionable results for the practice of investment management, especially the manager selection problem addressed by fund-of-funds. First, we show that investors seeking superior risk-adjusted returns from trend-following strategies should look for managers trading a large number and diversity of assets. These characteristics are key choice variables in designing strategies and are easy to compare among managers. Second, we show that funds trading fewer assets and sectors are far more likely to experience a wider range of outcomes. Of course, any large sample of funds will show at least some managers performing quite well, some due to skill, others due to luck. We show that investors should apply a larger discount to the outperformance of managers trading fewer assets, as the strength of mean reversion in performance among such managers is likely to be more intense. These findings are especially relevant in the evaluation of specialist managers focusing only on individual asset classes, or on managers trading only a few representative assets from each major sector. Such managers may be maximizing the liquidity of their investment process, but not necessarily its long-term sustainable alpha.

Compared to earlier academic research, our findings run counter to prior empirical studies of the benefits of diversification in portfolio management. Echoing other studies, Statman (1987), for example, finds that the benefits of diversification in long-only stock portfolios reach diminishing returns at around 30 to 40 stocks. Although our focus differs – Statman (1987) studies the diversification of risk, whereas our focus is also on return – the contrast with our results showing continued benefits at more than double the number of assets is striking (over 80 assets). We conjecture that this difference may arise from the differing levels of correlation of the assets and constraints used in the respective analyses. Whereas most analyses following Statman (1987) employ long-only positions in a single homogenous asset class, usually equities, our analysis features long and short positions in trend-following strategies applied to a wide variety of assets (equities, fixed income, currencies and commodities). While the benefit of one more

stock in an already sizable equity portfolio is likely to be nil, in Managed Futures the diversification opportunities are often far greater, given the use of disparate assets and asset classes, and the possibility of diverging trends across assets and sectors.

Our conclusions are more in line with the recent empirical results of Livnat et al (2017). Comparing the results of active stock pickers, they find that among top-ranked funds based on past performance, diversified funds outperform concentrated funds in the subsequent period, principally by providing more consistent returns and more favorable drawdown profiles. These findings echo our conclusions in Managed Futures, which show the benefits of diversification and that the apparent outperformance of more concentrated strategies should be heavily discounted.

II. Methodology

Our primary objective is to quantify the impact of diversification in a generic Managed Futures process. To do this, we adopt the methodology of Hurst (2013) whose simple time series momentum model successfully replicates the behavior of a typical Managed Futures fund, making it well suited for our use. We study the impact of naïve diversification by adding new assets and sectors to this simple strategy. To eliminate the effect of specific asset choices, we use simulations with randomly selected asset sets.

Building a generic managed futures process

Following Hurst (2013), our time series momentum strategy determines its desired exposure for asset i at time t as follows:

$$W_t^i = \frac{\text{sign}(r_{t-1\text{month},t}^i) + \text{sign}(r_{t-3\text{month},t}^i) + \text{sign}(r_{t-12\text{month},t}^i)}{3} \frac{10\%}{\sigma_t^i}$$

where $r_{t-X\text{month},t}^i$ represents the return of asset i over the past X month as of time t . The ex-ante annualized volatility estimate σ_t^i is based on the exponentially weighted average of past squared returns with a half-life (exponential decay) of 60 days. Once the desired exposure for each asset is determined, the overall portfolio is scaled to target an ex-ante volatility of 10% using a covariance matrix calculated with the same decay-weighted approach used to calculate volatilities. To be conservative, our backtest simulations delay implementation by one full day after the signal is calculated. For example, a desired exposure calculated using data as of Monday's market close is assumed to be implemented one day later, as of Tuesday's close. Our backtests are conducted daily to reduce the potential impact of noise associated with varying rebalancing dates and cycles. We report all of our returns gross of transaction costs.

Asset universe and sample period

We examine 89 tradable assets across all 4 major asset classes and 14 distinct sectors. As summarized in Table 1, these include: in equities, both developed and emerging market futures; in fixed income, short-term (1yr) rates, long-term rates (10yr), yield curve slopes (10s vs 2s and 30s vs 10s), and emerging rates; in currencies, both developed and emerging forwards, and in commodities, futures in energy, precious metals, industrial metals, grains, livestock, and softs.

Table 1: Assets Included in Strategy (89 assets across 4 asset classes and 14 sectors)

EQUITIES	FIXED INCOME	CURRENCIES	COMMODITIES
Developed Equities	Short-term Rates	Developed Currencies	Energy
ASX SPI 200	EUR 1y rate	AUD/USD	WTI Crude
S&P/TSX Comp	SEK 1y rate	CAD/USD	Brent Crude
CAC 40	GBP 1y rate	EUR/USD	Heating Oil
DAX	USD 1y rate	JPY/USD	Natural Gas
HANG SENG	Long-term Rates	NOK/USD	Gasoil
FTSE/MIB	CAD 10y rate	NZD/USD	RBOB Gasoline
TOPIX	EUR 10y rate	SEK/USD	Precious Metals
NASDAQ	JPY 10y rate	GBP/USD	Gold
AEX	SEK 10y rate	Emerging Currencies	Silver
NIKKEI	CHF 10y rate	BRL/USD	Industrial Metals
IBEX 35	GBP 10y rate	CLP/USD	Aluminum
OMX STKH30	USD 10y rate	COP/USD	Lead
FTSE 100	Slope	CZK/USD	Nickel
S&P 500	EUR 10y-2y slope	HUF/USD	Copper
Emerging Equities	JPY 10y-2y slope	IDR/USD	Zinc
HSCEI	GBP 10y-2y slope	INR/USD	Grains
SGX Nifty 50	USD 10y-2y slope	KRW/USD	Corn
KOSPI 200	EUR 30y-10y slope	MXN/USD	Soybean
TOP 40	JPY 30y-10y slope	PLN/USD	KC HRW Wheat
SET 50	GBP 30y-10y slope	RUB/USD	Wheat
BIST 30	USD 30y-10y slope	ZAR/USD	Livestocks
MSCI Taiwan	Emerging Rates	TRY/USD	Feeder Cattle
	CZK 5y rate		Live Cattle
	HUF 5y rate		Lean Hogs
	PLN 5y rate		Softs
	ZAR 5y rate		Cocoa
			Cotton
			Coffee
			Sugar

Our analysis spans the 16-year period from January 2000 to December 2016. More than 90% of our assets are available for the entire period, and every asset has at least 13 years of data. Given that the objective of our paper was to study the impact of diversification as a function of the number of assets, we focused on creating the largest possible asset universe across a long period to capture the dynamics of Managed Futures strategies implemented widely over a full market cycle. Nevertheless, we note that our conclusions remain valid using smaller asset universes with longer sample periods. The returns of these assets are used as inputs to our Managed Futures strategy simulations. Appendix 1 illustrates the strategy information ratio sorted by raw asset Sharpe ratio.

Simulating naïve diversification

Our simple time series momentum strategy embeds two risk-sizing mechanisms. First, each asset is scaled individually at each rebalance date to a fixed ex-ante risk. As a

consequence, any two assets with the same momentum signal strength will take the same amount of risk. This is useful for our analysis since each asset added to the program will contribute the same amount of risk as any other, and consequently increase diversity incrementally and uniformly. We call this “naïve” diversification because it does not adjust for correlations among assets. The second risk adjustment simply scales the overall portfolio to target a fixed ex-ante risk using the covariance matrix. This does incorporate correlations among assets, but does not change the level of diversification since the individual assets’ relative weights are left unadjusted. Nevertheless, this step is useful because it facilitates direct comparison of non-risk adjusted statistics such as returns and drawdowns.

Finally, we simulate hundreds of random combinations of assets to form portfolios of various sizes (a portfolio of 1 asset, through a portfolio of 89 assets). By doing this, we can simulate over 5000 combinations of strategies, each spanning 16 years (over 2 million portfolio rebalances in total). One benefit of this simulation approach is that it allows us to eliminate the effect of performance differences across assets. As well, it mimics how different hypothetical Managed Futures programs might perform if (1) the managers were allowed to hold only a fixed number of assets and (2) they had no ability to predict future performance by asset.

Continuing with this analogy, a slightly more sophisticated manager might choose to diversify his or her program by selecting assets from different asset classes or even sectors. To model this behavior, we conduct additional simulations that select assets from distinct asset classes or sectors. For example, we have 4 asset classes and 14 sectors in our tradable asset universe. Given this, an “asset class diversified” simulation with 16 assets will have 4 randomly selected assets from each asset class. Analogously, a “sector diversified” simulation with 28 assets will have 2 randomly selected assets from each sector. Our findings are based on the distributions of the performance statistics generated by these simulations.

Methodology limitations

Before discussing the results, we would like to acknowledge certain limitations of our methodology. First, our use of ex-ante risk scaling might dilute potentially useful information in the signal magnitudes. For example, in the extreme case in which our simulation employs only one asset, our process will produce the same exposure regardless of signal strength. While this issue can be squarely addressed through the use of long-term risk budgets, we decided to adopt this limitation, following Hurst (2013), to avoid the possibility of look-ahead bias.

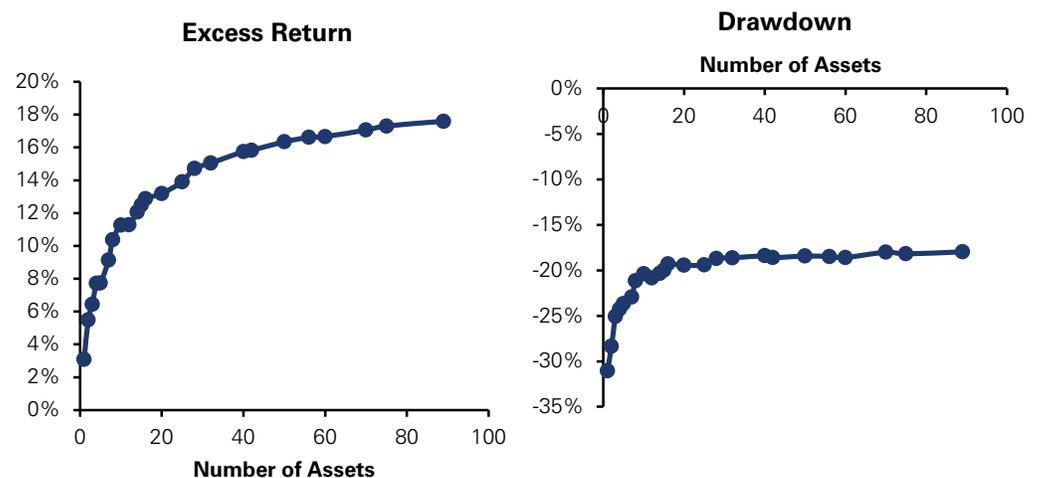
Second, expanding the asset universe with assets chosen randomly may lead to trading relatively less liquid assets. We acknowledge this may be a problem for less sophisticated managers without modern execution capabilities, and for managers with extremely large assets under management. At the same time, however, note that we selected the expanded universe of assets to be liquid from an absolute perspective, in order to provide a sound indication of the trading opportunities available for many managers. We also note that by spreading risk, the individual positions tend to be smaller, potentially making the overall program more nimble and easier to implement.

III. Naïve Diversification with More Assets

Impact of adding more assets

Figure 1 illustrates primary performance and risk statistics, averaged across simulations. With the process held constant, adding assets materially improves results. As expected, the marginal benefit of an additional asset is greatest when the number of assets is low. While risk-adjusted returns improve across all starting points, the benefits to the drawdown profile appear to bottom out after approximately 30 assets. As shown in Appendix 2, the relatively stable realized volatility profile indicates that our ex-ante volatility scaling is effective on average, and not significantly affected by the number of assets included in the hypothetical portfolios. Similarly, the simulated strategies' correlation with primary assets are relatively unaffected by the number of assets and remain low.

Figure 1. Average Performance Statistics vs. Number of Assets (additional statistics in Appendix 2)



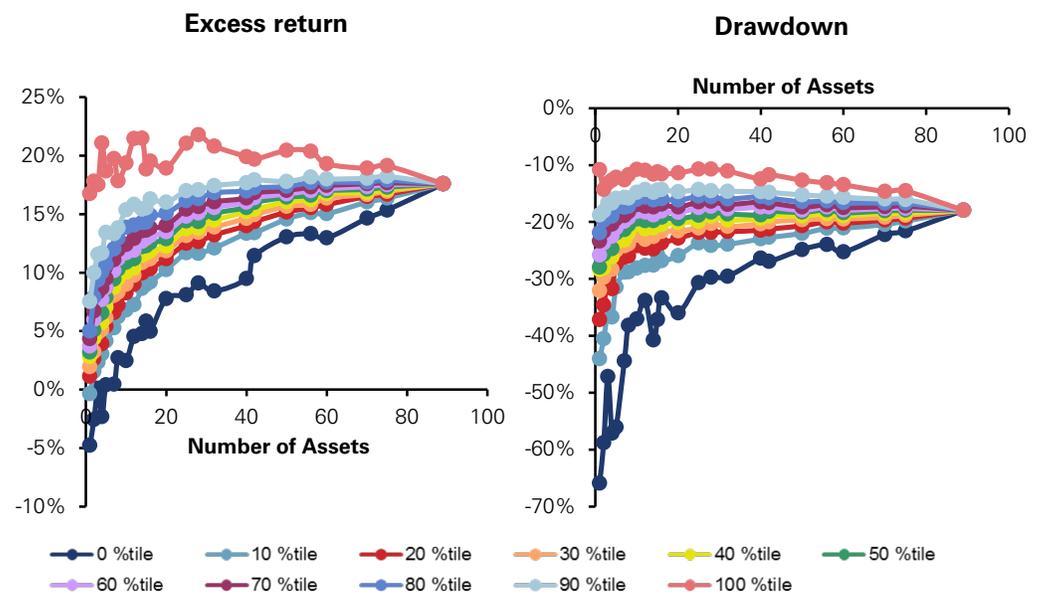
Source: GSAM

In Figure 2, we show the percentiles of the same performance statistics drawn from the distribution of outcomes provided by our simulations. The implications here are again in line with the conclusions based on the average values discussed earlier. As important, they also show the significant dispersion in potential outcomes, especially when fewer assets are employed. One interpretation of this result is that funds trading fewer assets will need far greater skill to offset the very strong and reliable benefits of diversification. Compare for example two managers, one trading the full set of 89 assets, another trading just 30. In order for the latter manager to achieve the same information ratio as the former, they will have to exhibit top decile performance. This is an extremely high hurdle, especially when the far simpler alternative is to diversify, and choose to trade additional assets.

In this same vein, our results make clear that funds trading a limited universe of assets may outperform more diversified programs simply due to luck. Because such occasions are evident during our simulation spanning 16 years, it suggests that such occurrences

are even more likely over shorter time periods, often of the length that are available to evaluate extant managers. Appendix 4 illustrates this point more concretely by showing the distribution of excess returns over 9 sub-periods. In each of these sub-periods, we have some concentrated funds that outperform the diversified program by sizable margins. For example, the best concentrated funds in each sub-period outperformed the diversified program by 12% on average with a maximum outperformance of 22%. It is worth noting that these outperformances are artifacts of our randomized simulation analysis and not always attainable in practice. Our illustration also highlights the significant potential risk associated with concentrated funds. On average, the worst performing concentrated funds underperformed the diversified processes by -23% (annualized). Investors should consider this statistical fact when reviewing past performance of concentrated Managed Futures programs.

Figure 2. Distribution of Performance Statistics vs. Number of Assets (additional statistics in Appendix 3)



Source: GSAM

Impact of adding more assets from different sectors and asset classes

Appendix 5 shows the benefits of adding new assets from different sectors or asset classes while holding the overall number of assets constant. As the total number of assets can only grow by the multiples of available asset groups, our analysis in this case is less granular. We also focus on simulations involving relatively few assets, which is necessary because our overall universe is fairly balanced by asset group. As a consequence, even our fully randomized base portfolio will tend toward balanced allocations within and among asset groupings when the required number of assets in the portfolios is large.

Nevertheless, our simulations clearly indicate that the average information ratio is higher for portfolios that are explicitly diversified across asset classes or sectors. The average drawdown also improves with larger improvements in sector-diversified simulations. The correlation with primary assets remains unaffected by this additional constraint.

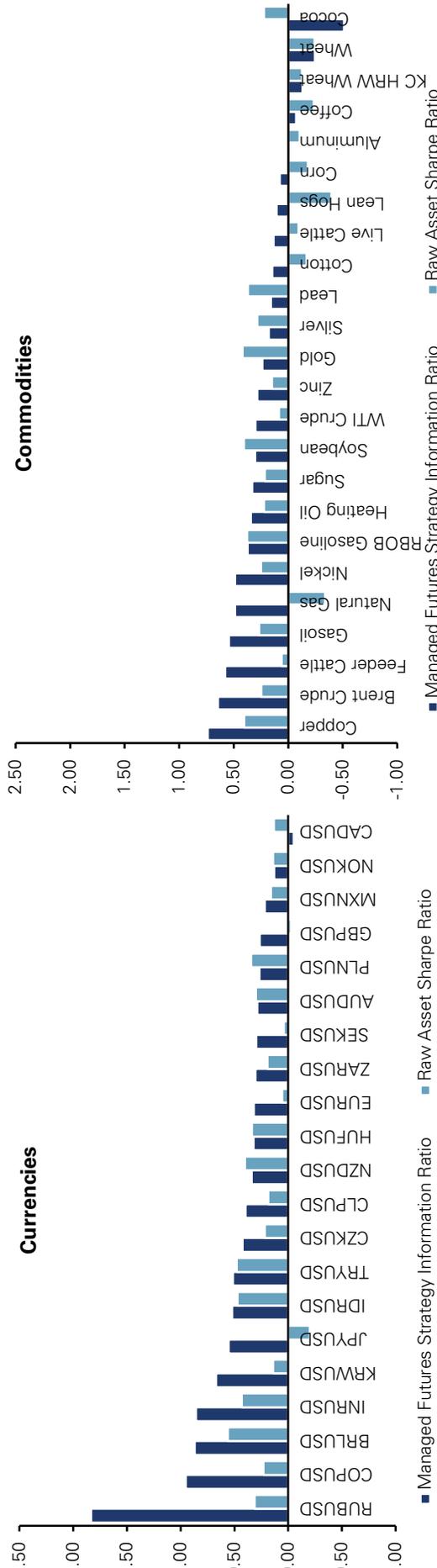
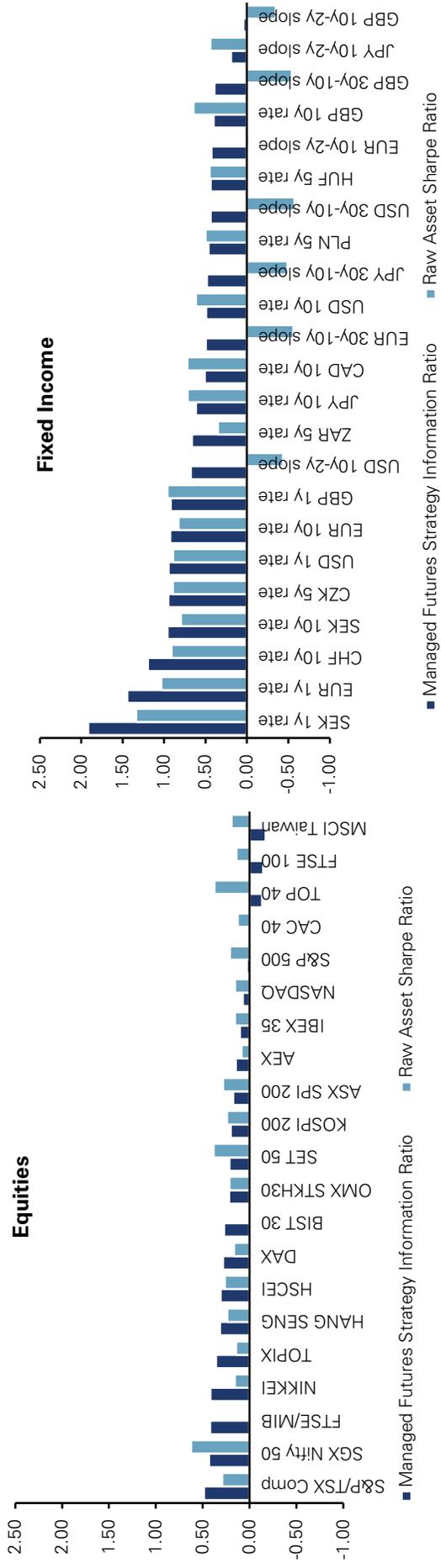
IV. Conclusion

It is well-established from financial theories that portfolio diversification is a mathematical free lunch. In this paper, we have specifically quantified its benefits in the context of Managed Futures strategies using a simulation environment based on an extensive asset set and a lengthy evaluation period. Evidently, additional assets and a more diversified risk budget consistently generate higher risk-adjusted returns. As expected, the benefit increases as more distinct assets are introduced to the program.

Our findings are also in line with the economic rationale of the strategy. While all markets are subject to common behavioral biases and human tendencies, market segmentation and unique risk drivers for each market will create uncorrelated trading opportunities. Diversification, in all its forms, allows Managed Futures to harvest returns with reduced exposure to idiosyncratic asset shocks. Conversely, a strategy that depends on only a few such opportunities, though successful on average, may frequently disappoint as other market factors overwhelm the predictive power of the trend model, especially over a short time horizon.

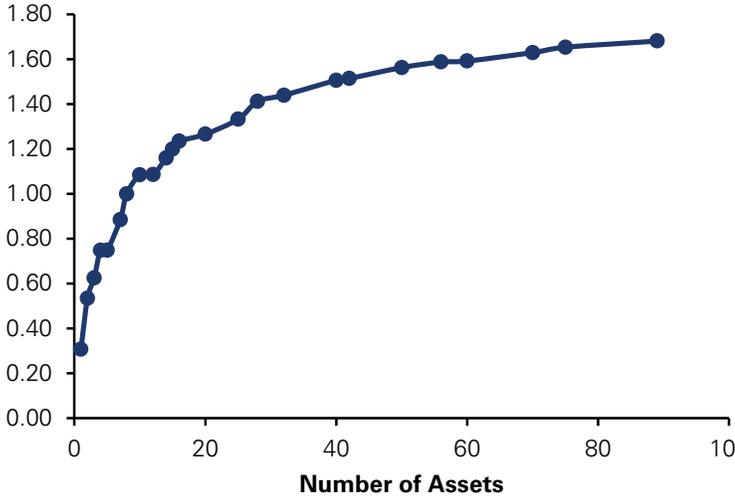
The implications for investors in Managed Futures funds, and fund-of-funds investors in such strategies, are clear. All things equal, they should select funds with more diversified programs. Our results also suggest that investors should on average expect lower risk-adjusted returns when investing in Managed Futures products with limited asset universes. Although such products may partially diversify a Managed Futures portfolio involving many managers, the adverse effect of netting risk on incentive fees should be carefully evaluated.

Appendix 1. Managed Futures Strategy and Raw Asset Performance

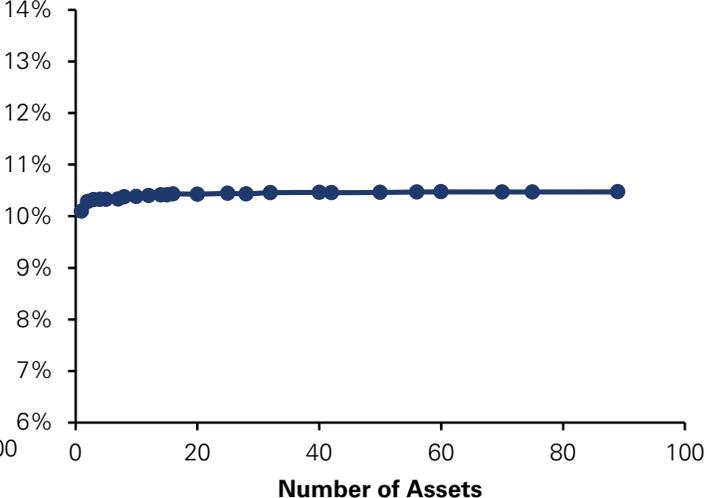


Appendix 2. Average Performance Statistics vs. Number of Assets

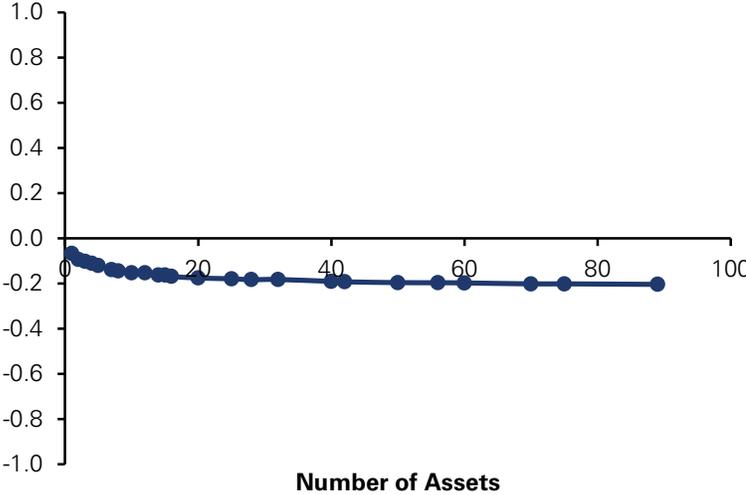
Information Ratio



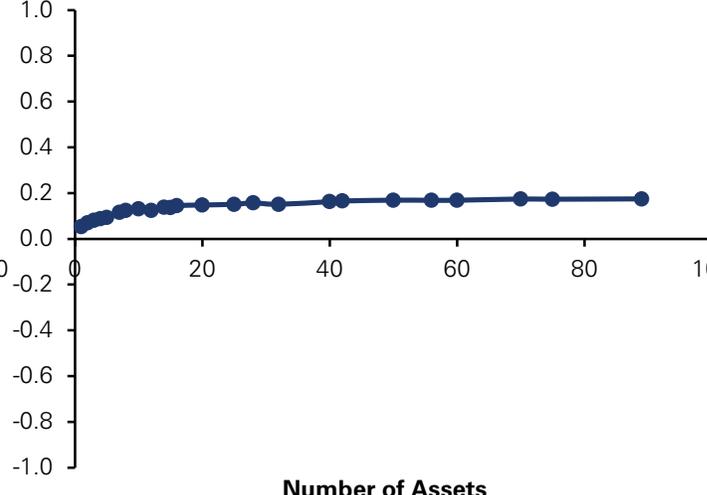
Volatility



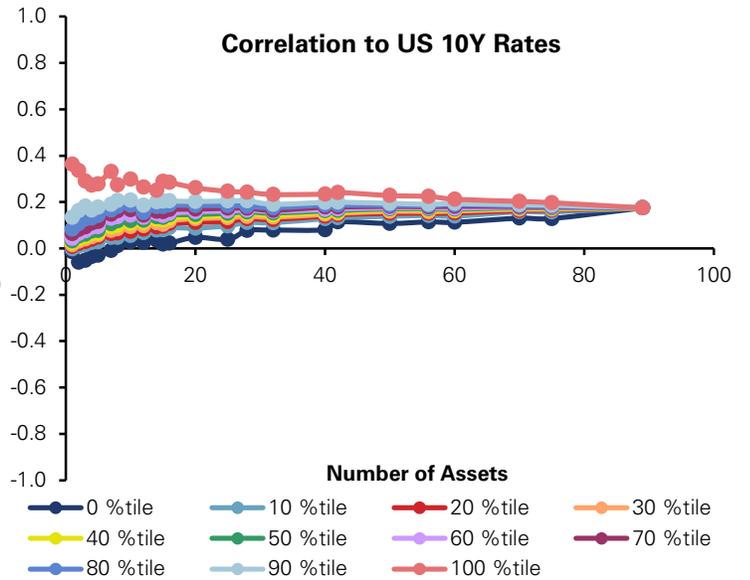
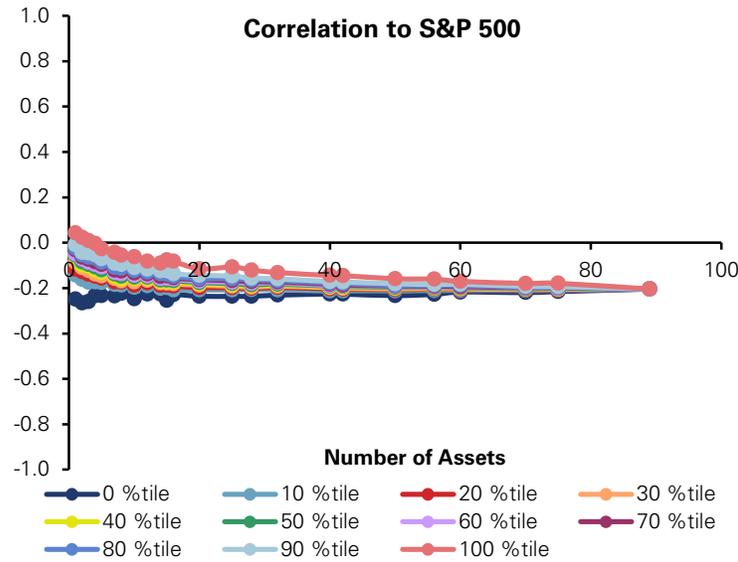
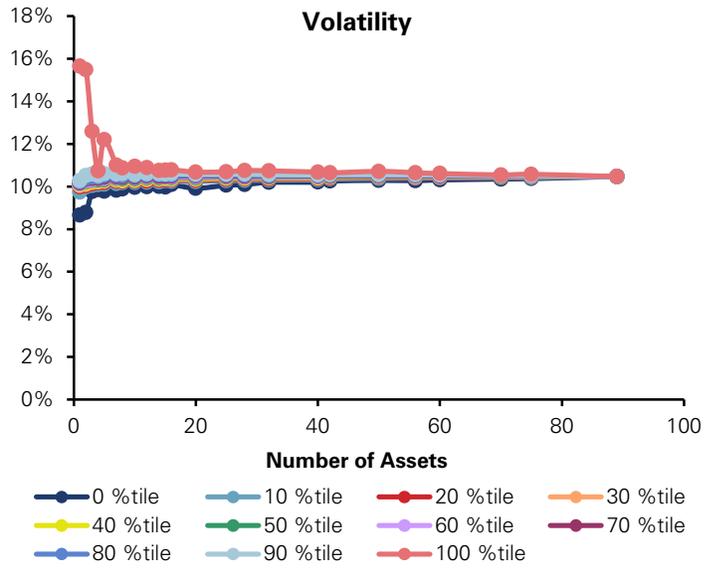
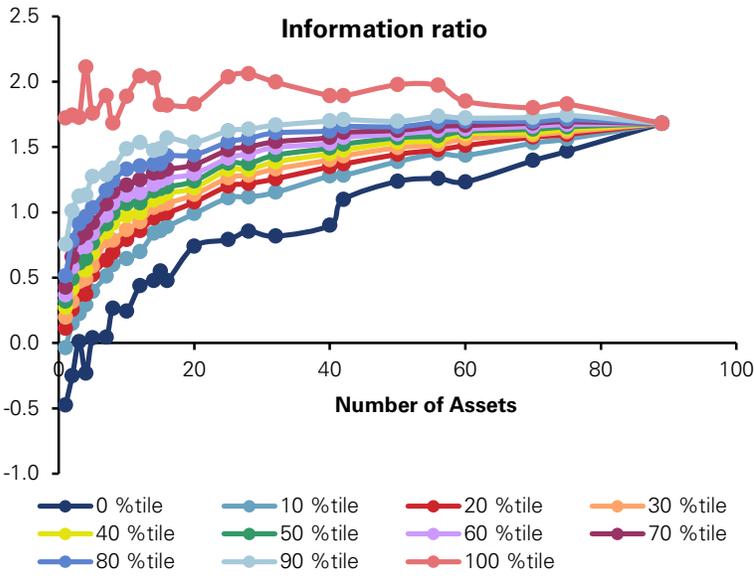
Correlation to S&P 500



Correlation to US 10Y rates

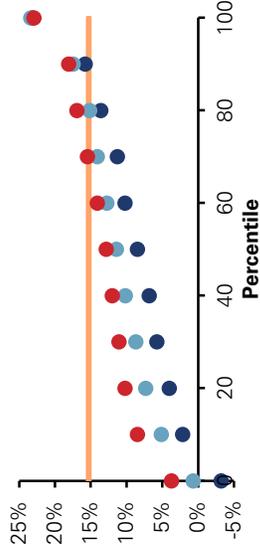


Appendix 3. Distribution of Performance Statistics vs. Number of Assets



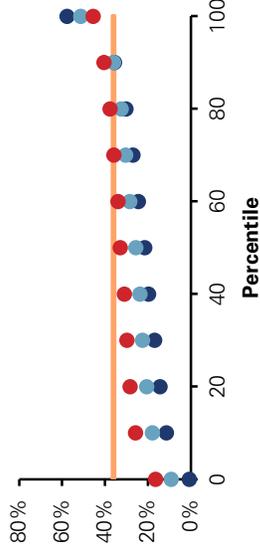
Appendix 4. Distribution of Excess Return over Various Sub-periods for Different Numbers of Assets

2000-2001



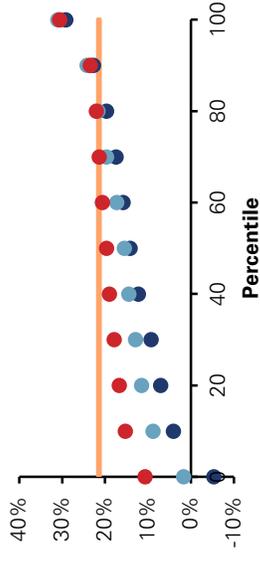
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2002-2003



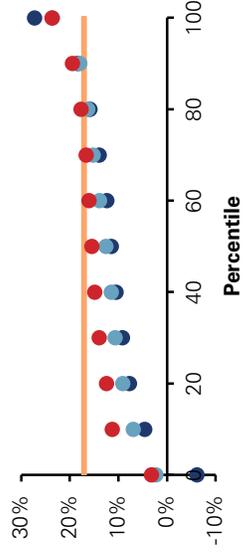
● 10 ● 20 ● 40 ● Full Universe

2004-2005



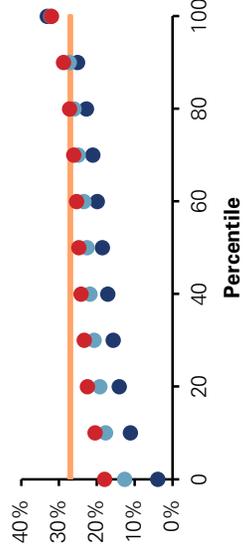
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2006-2007



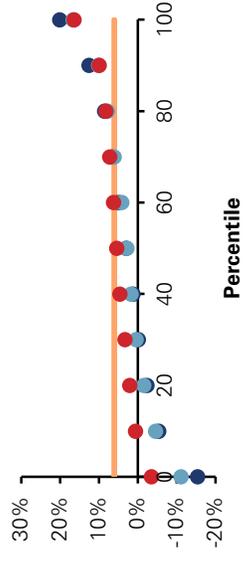
● 10 ● 20 ● 40 ● Full Universe

2008-2009



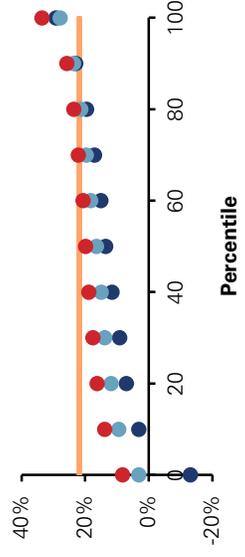
● 10 ● 20 ● 40 ● Full Universe

2010-2011



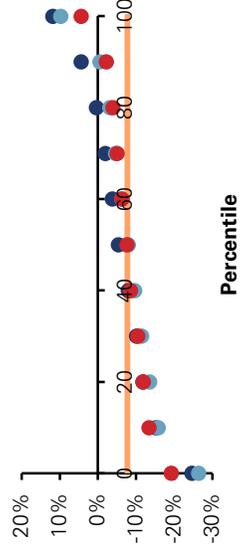
● 10 ● 20 ● 40 ● Full Universe

2012-2013



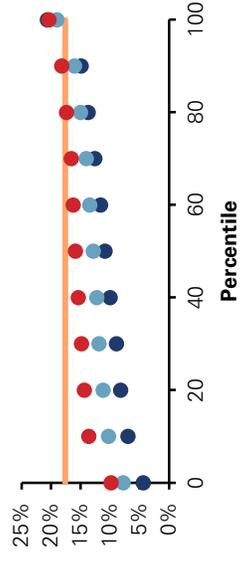
● 10 ● 20 ● 40 ● Full Universe

2014-2015



● 10 ● 20 ● 40 ● Full Universe

2016-2016

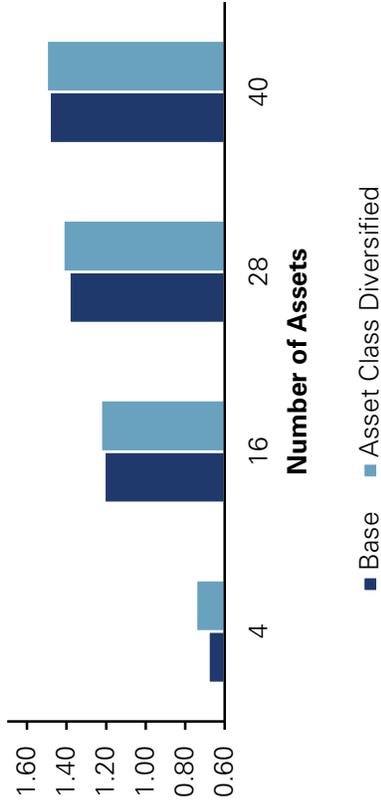


● 10 ● 20 ● 40 ● Full Universe

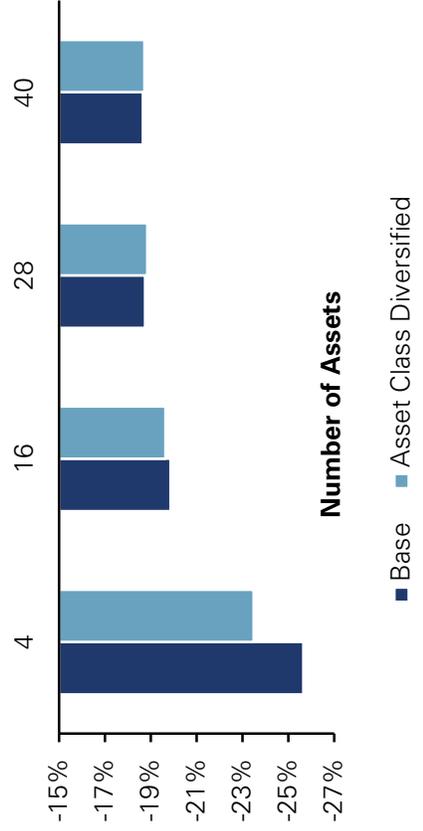
Appendix 5. Asset Class and Sector Diversified Portfolios - Average Statistics

Asset Class Diversified

Information Ratio

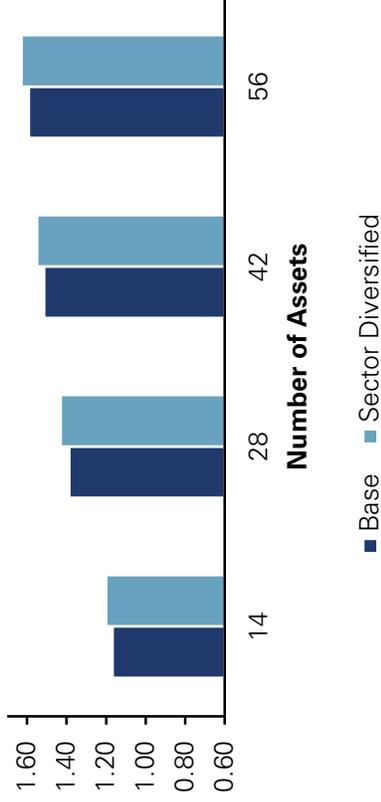


Drawdown

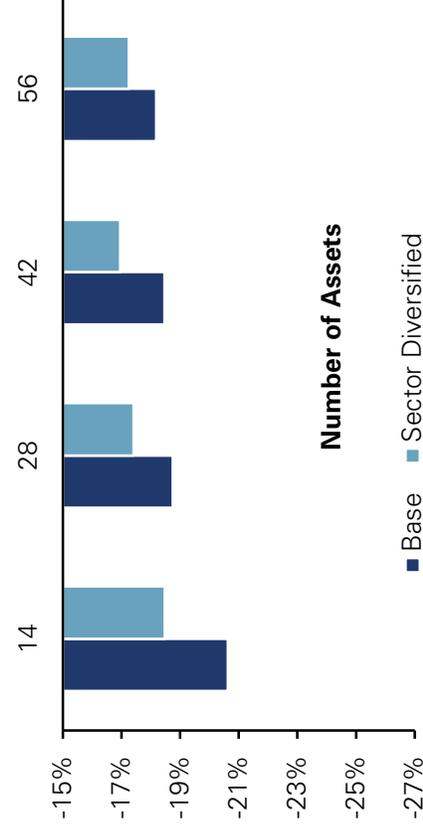


Sector Diversified

Information Ratio



Drawdown



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Effect of Fees:

The following table provides a simplified example of the effect of management fees on portfolio returns. Assume a portfolio has a steady investment return, gross of fees, of 0.5% per month and total management fees of 0.05% per month of the market value of the portfolio on the last day of the month. Management fees are deducted from the market value of the portfolio on that day. There are no cash flows during the period. The table shows that, assuming all other factors remain constant, the difference increases due to the compounding effect over time. Of course, the magnitude of the difference between gross-of-fee and net-of-fee returns will depend on a variety of factors, and this example is purposely simplified.

Period	Gross Return	Net Return	Differential
1 year	6.17%	5.54%	0.63%
2 years	12.72	11.38	1.34
10 years	81.94	71.39	10.55

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