Handelsmeisterei
Systematic Trading — Made In Germany

In Search of Diversification by Selecting Strategy Parameters

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Diversification is one of the most important tools for a systematic trader. This article will dive into the diversification possibilities of one simple strategy via different parameters. The article will both discuss the theoretical foundations and apply these to a real-world strategy under realistic assumptions about commissions, spreads and roll costs.

Diversification comes in different shapes and forms. As a systematic futures trader you immensely profit from the wide range of underlying assets available. You can not only trade all the major equity indices, but also foreign exchange rates, bonds, energy, metals, agriculture and even volatility. Future markets are simply the most diverse markets out there.

This source of instrument[1] diversification is the most powerful for any futures trader. A second source of diversification is the use of multiple trading strategies. To name a few, for example you can trade trend, mean reversion or carry.

A third source of diversification lies in the different time frames your strategy trades. Trend plays out over weeks, months or even years.

The same strategy can be deployed across multiple time horizons, allowing several parameterizations to trade simultaneously. This source of diversification is usually the weakest form of diversification of these three, but nevertheless worth pursuing as we shall see in this article.

Before opening the math toolbox, let's first ask whether diversification is really always a good thing.

You may have heard the argument that it is necessary to run a concentrated portfolio to be successful. There are enough examples of that out there. Look at Warren Buffett: He did not get famous for investing in a broadly diversified index like the S&P 500!

You also may have heard the argument that being as diversified as possible is the best thing ever, because diversification is the only free lunch in finance.

This argument also has its problems. You just have to look at the stock performance of conglomerates. Of course, corporate diversification and portfolio diversification are not the same thing. Nevertheless, the persistent conglomerate discount illustrates an important principle: diversification is not free when it introduces additional complexity.

Everybody who has worked for some time in a large organisation usually experienced it first hand: Increased complexity and larger hierarchies impose an even larger toll on operative decisions.

Diversification should be viewed more carefully. It is not always the right answer. Ultimately it is a trade-off between focus and complexity.

1. In this article a future trading a particular underlying asset is called an instrument. There are cases where the same asset is traded as two different instruments, like trading two different sizes of the same underlying. For example, constellations like this exist for micro and full size contracts. For purpose of this article, instrument and asset are used synonymously.

If you are a systematic trader that develops special models for interest rates the added complexity to do the same for the agricultural markets may be too much. But if you run models on daily data that do not differentiate between asset classes, more diversification is a no-brainer.

Unlike adding entirely new strategies, trading additional instruments or additional parameters of the same strategy often increases complexity only marginally. The remainder of this article explores whether the resulting diversification benefits justify doing so.

Theory

Let's look a little bit deeper into diversification from a mathematical standpoint. Diversification manifests itself if you combine return streams that are not perfectly correlated. To keep things simple we combine the return streams of two strategies with the same expected return of 15% and a volatility of 20% each. Further assume that the correlation between the two is 50% and we will put half of our capital in each of them.

The volatility of a two-strategy portfolio can be calculated by:

$$\sigma_p = \sqrt{w_1^2\sigma_1^2 + w_2^2\sigma_2^2 + 2w_1w_2\rho\sigma_1\sigma_2}$$

with w_i denoting the weight of each strategy. In our case of equal weighting, $w_1 = w_2 = 0.5$. The symbol σ_i denotes the volatility of each strategy i (each 20% in our case). Finally, ρ is the correlation between the two (50%).

For two equally weighted strategies with the same volatility, above formula can be simplified to:

$$\sigma_p = \sigma\sqrt{\frac{1+\rho}{2}}$$

The relationship between the portfolio volatility and the correlation is visualized in figure 1. As can also be seen from the formula, the resulting portfolio volatility is always lower than the volatility of the component strategies if they are not identical.

Especially for futures traders this is the magic of diversification. In the above example you get the same return — 50% of capital in strategies yielding 15% each results in a portfolio with a return of also 15%. But the volatility (or risk) of the portfolio drops to 17%. The Sharpe ratio of combining these two strategy therefore rises from 0.75 to 0.87.

Figure 1: Relative portfolio risk reduction as a function of strategy correlation. The two strategies are combined by putting 50% of the capital in each of them.

Because futures are leveraged instruments it is way easier for futures traders to control their portfolio volatility. You are able to crank up the return if you prefer to have a risk level of 20% instead of having the same return but a lower risk of 17%.

The diversification you get is roughly linear for strategies with a correlation between -50% up to +100%. In reality finding strategies that are correlated below -50% and have positive expectancy is quite uncommon.

Nevertheless this quasi linear relationship is quite a driver of performance. With two uncorrelated strategies (correlation 0%) you get a risk reduction of 30%. But even with a correlation of 50% you still get a risk reduction (or performance increase) of still 13%. That's an impressive relationship!

Before you get too excited, let us discuss the formula in practice. Unfortunately none of the parameters in the formula are stable in practice. Especially correlations of underlying assets tend to increase together in financial situations of stress. In such a situation, everybody tries to sell and all assets fall together and your assumed diversification effect breaks down.

Mathematically the correlation also only captures linear relationships between assets. That's something to keep in mind — think about it more as a rough measurement about how much two time series move together. The real relationship between them is also most likely not linear.

There are other models out there that try to capture relationships between time series like copulas or cointegration but they also have assumptions that are questionable in reality and use more parameters — and that is something to avoid unless there are very strong incentives in doing it.

But even the volatility of a strategy is an unknown quantity that may exhibit wild swings. So please don't take this formula too literally and crank up the leverage like there is no tomorrow! This even happened to the very smart people of Long-Term Capital Management (one of them even a Nobel laureate) — you can read about this in the excellent book of Roger Lowenstein *When Genius Failed*.

Take this concept more as a guide to improve your trading system and know about different sources of diversification. This way you can profit from the concept without lulling yourself into a false sense of security.

Let's meet Reality

So far we have learned that diversification works in theory.

The interesting question is whether parameter diversification behaves the same way in a real trading system.

We will do so by applying it to a real-world strategy: Cross-sectional momentum from Robert Carver's book *Advanced Futures Trading Strategies*.

What is cross-sectional momentum? It captures a signal from an asset that out- or underperforms other assets in its group.

Let's say you grouped your tradeable equity indices by country and the US-listed tech-heavy Nasdaq index outperforms the broader S&P 500 over a longer period due to some tech revolution especially tech companies profit from.

That's an example of cross-sectional momentum. Some underlying factor plays out better over a time period for one specific asset than other assets in the same group — in this case better compared to other broader US indices.

At first glance, this sounds like a meaningful strategy we can work with, because the economic rationale makes sense. This is a very important first step in strategy design and should never be skipped. Don't just run backtests for some formulas and pick the strategy, that performed best in a backtest. That is a recipe for disaster!

Cross-sectional Momentum

Let's define a trading strategy around this economic intuition:

Objective

Profit from out- or underperformance from an asset relative to the group of assets it is associated with.

Definitions

$$P_t^{Norm} = \sum_{i=0}^{t} \frac{100 \times (P_i^{Close} - P_{i-1}^{Close})}{\sigma_i^{Price}}$$

P_t^{Norm}: Normalized price of an asset at time t. Prices are normalized to make prices of different assets comparable with each other by cumulating their daily price changes. At time t=0 the normalized price of each asset is 0.

P_i^{Close}: Backadjusted close price for an asset at time i

σ_i^{Price}: Price volatility at time i. It is used to normalize the price series so that the daily price moves are expressed in terms of daily volatility. This way very volatile assets like Bitcoin can be compared to quieter ones like bonds.

$$A_t^{Norm} = \sum_{i=0}^{t} \text{Ø} \left(P_{j,t}^{Norm} - P_{j,t-1}^{Norm}\right)$$

A_t^{Norm}: The normalized price of an asset class at time t. Its return per day is the average (normalized) return of its constituents j. The price of the whole asset class is then simply sum of these averages up to time t.

$$R_t = P_t^{Norm} - A_t^{Norm}$$

R_t captures the out- or underperformance of an instrument versus the average of all other instruments in its group at from time t=0 up to time t.

$$\text{outperformance}_s = \frac{R_t - R_{t-s}}{s}$$

R_{t-s} captures the out- or underperformance of an instrument versus the average of all other instruments in its group from time t=0 up to time t-s. The parameter s is called the lookback period in trading days.

outperformance_s calculates the out- or underperformance of an asset relative to its group during the last s trading days. The outperformance is normalized by s to express the performance per trading day. This makes trading signals for different parameter choices of s comparable among each other.

This formula essentially calculates the average performance of an asset compared to its peers over s days. If it is positive the asset outperformed its peers and we want to be long that asset.

Trading Signal

$$\text{signal}_t = \text{ewma}_{s/4}\left(\text{outperformance}_s\right)$$

signal_t Finally, the trading signal results from smoothing the outperformance. The smoothing is done by an exponentially weighted moving average ewma so that it does not jump too much between each trading day. The smoothing factor used is s/4 and expressed as a ”span” like in python’s ewma functions.

This continuous trading signal has to be converted to actual trading positions and each of the instruments can be traded separately. Let’s not bog down in further details like only trading instruments that are cheap enough (commission or spread wise) and trade just all of them.

The more instruments you trade, the more diversification you get. Figure 2 shows my current universe of tradeable instruments over time. The historic data of the universe starts in June 1975. Back then there were only a few classic futures like soybeans or US bonds.

Over time the futures market got more and more diverse, new instruments entered the market, some of them successful others have been discontinued (like the famous pork bellies). In aggregate, more and more instruments have been tradeable over time.

Now let's plug the cables directly in the wall and trade all of them available at each point in time. To do that, we actually need to decide which lookback period s to use for our cross-sectional momentum strategy.

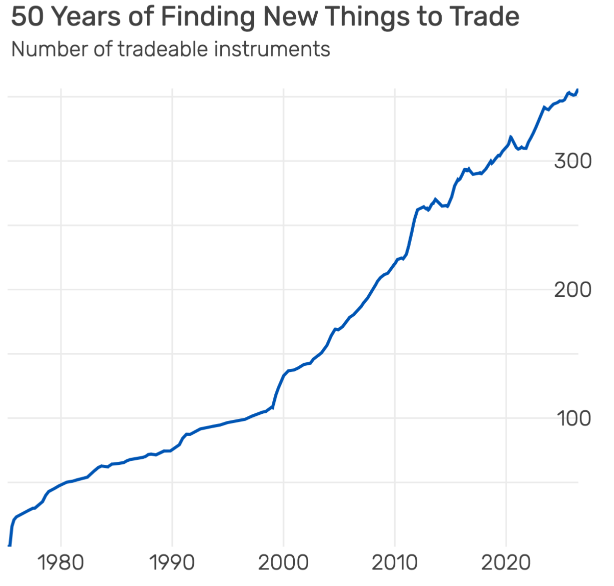

Figure 2: Number of tradeable instruments over time. An instrument is classified as tradeable if it satisfies market data and liquidity constraints. Smoothed for readability.

Which lookback period should we choose? Twenty days? One hundred days? Are there time frames that do not work at all? This turns out to be surprisingly difficult.

The Parameter Surface

Without looking at any backtests, it is clear by the definition of the signal that shorter time frames will trade more often because R_t will be more volatile due to a shorter relevant history. It will therefore vary more from day to day and may switch between long and short more often.

This will incur higher trading costs and most probably impact performance. To get a better feeling for the signal, let's run backtests for a range of different lookback periods s.

If parameter diversification is going to work, we first need a strategy whose performance is reasonably stable across parameters. Figure 3 shows the Sharpe ratios for a range of lookbacks between 20 and 350.

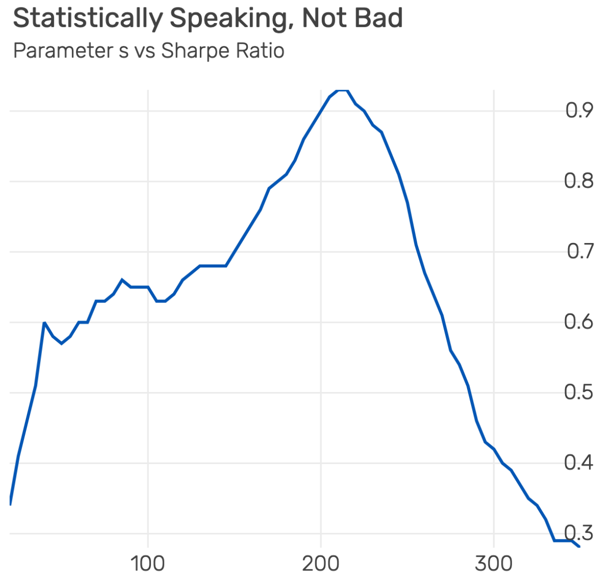

Figure 3: Lookback period from 20 to 350 in steps of 5 of the cross-sectional momentum strategy and the corresponding Sharpe ratios. The Sharpe ratio is calculated without a risk free rate but includes all trading costs.

Now that is quite something! It is a trading signal that works pretty well: The signal has a Sharpe ratio of about 0.5 or higher for a parameter range from about 30 to 280. That is actually a very important property of any worthwhile strategy. If the parameter surface is very noisy, you either have not enough instruments in your universe, the signal is not defined in a stable way or it is not good in general.

Consider one particular strategy of the whole flock: Lookback period s=215. This is the best strategy with a Sharpe ratio of 0.93. Its equity curve and drawdown is shown in figure 4.

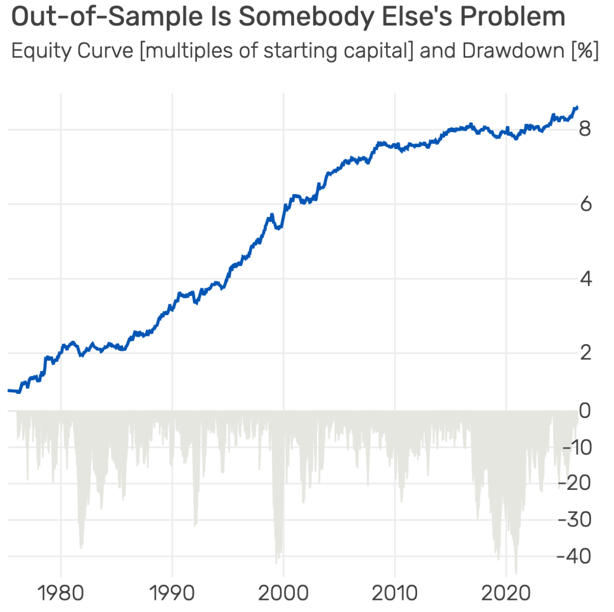

Figure 4: Equity curve and Drawdown of best cross-sectional momentum strategy with lookback s=215. No compounding, starting capital is 1 and risk target 25%.

There are several important observations of this graph. The performance seems to deteriorate after about the year 2010. Bad drawdowns are about -40% and especially pronounced in duration after 2010.

Let's have a look at some performance statistics of this parameter from table 1:

Especially the large drawdown duration of the strategy is of some concern. A whopping 1837 days, that's over 5 years! The small positive skewness of the strategy is an interesting property. On the negative side, the return stream of this lookback period has fatter tails on the downside than the upside.

Statistic	Value
Return after Costs [% p.a.]	14.77
Sharpe	0.93
Maximum Drawdown [%]	44.87
Avg Drawdown Duration [days]	33.08
Max Drawdown Duration [days]	1837
Monthly Skew	0.13
Lower Tail	1.43
Upper Tail	1.27
Winning Days [%]	53.35
99% Historical VaR [%]	77.74

Table 1: Performance statistics of best cross-sectional momentum strategy with lookback s=215

Selecting Parameters

Should you trade this particular parameter, because it is the best? This is precisely the point where inexperienced quants get it wrong. The lookback of s=215 is the best lookback period in a finite sample of historical data. If you do this optimization over a subset of instruments or only parts of your history, it will not be the best any more.

Nevertheless there seems to be something there. The performance increases steadily from a lookback of around 30 up to the maximum of 215 and then decreases again. Cross-sectional momentum seems to play out on a bigger range of time frames.

A sensible approach is to trade several parameters of this strategy. But which ones? We need a better framework to make a decision.

If you remember the introduction, we may also kill several birds with one stone. As the return streams of different parameters are not perfectly correlated, we get some diversification and can trade a range of cross-sectional momentum without committing us to just one time frame.

We can answer this by computing a correlation matrix of the return streams of the different parameters. Figure 5 shows just that. You may notice that especially larger values of the lookback period s are higher correlated than lower values.

The explanation for this lies in the design of the trading signal. The signal for the lookback period s=345 shares 345 (98%) data points with the signal for s=350. Therefore all the outperformances of these neighboring parameters will be quite similar. Some shorter lookbacks like s=20 on the other hand share only 15 (75%) of their data with their neighbor s=15. The exponential weightning has another decay for each of the parameters but will not transform shared data in something totally different.

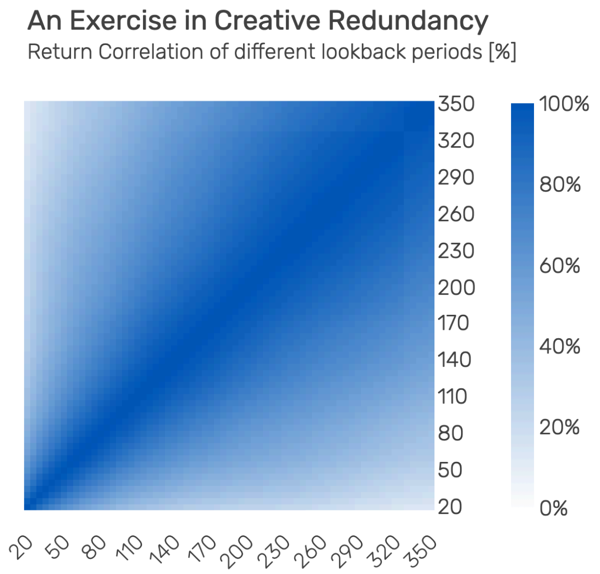

Figure 5: Correlations between returns of cross-sectional momentum with lookback periods s from 20 to 350 in steps of 5.

Because of this it is not advisable to trade all of the parameters. Doing that results in overweighting the larger parameters.

One approach is to trade parameters that have a maximum correlation between them. Which threshold you choose is not that important. Each has the property that you will trade less of the higher correlated large parameters. I will use a maximum correlation of 95% between neighboring parameters and want to capture strategies with a Sharpe ratio of 0.6 or higher.

The relevant parameter range comes down to lookbacks between 40 and 270. Starting with 270 and then searching for the next parameter with a correlation of 95% or less and repeating this procedure you end up with the parameter set of 270, 230, 195, 165, 135, 110, 90, 75, 60 and 45.

As you are reading an article from Systematic Trading—Made in Germany, I will step into my country's tradition of over-engineering and also provide you with the algorithm to select parameters to trade from a given range.

Objective

Find parameters from a given parameter surface

Input

Eyeball a parameter range (lower and upper bound) from the parameter surface. Ideally, the Sharpe ratios within the range should be stable and high enough to provide value. This decision is dependant on other strategies you trade. I typically look for a range with a Sharpe ratio of 0.6 or higher. It can be lower if you develop a strategy that has a low correlation to other strategies you trade.

Algorithm

```
params <- c(lower, ... , upper)
result <- c(upper)
param <- upper
while (param >= lower) {
 if (cor(param, result[1]) < 95%) ·
  selected <- c(param, result)
 }
 next param
}
```

The equity curve and drawdown of the particular set of parameters is shown in figure 6 and table 2 shows some statistics of the strategy.

If you compare table 2 with the statistics of the best strategy of table 1, you will find that the strategy with a mix of lookback periods is worse than the best strategy: The Sharpe ratio drops from 0.93 to 0.83 and the maximum drawdown increases to 50%. The skew and tail properties are about the same, only the maximum drawdown duration decreased by over a year.

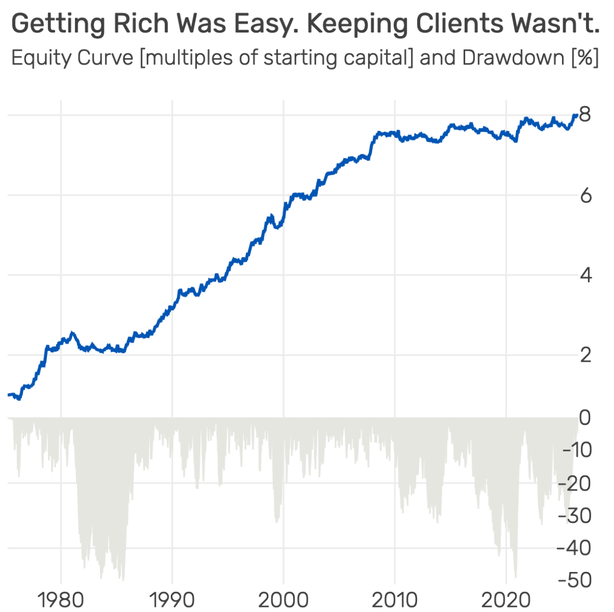

Figure 6: Equity curve and Drawdown of cross-sectional momentum strategies with a mix of lookback periods. No compounding, starting capital is 1 and risk target 25%.

Statistic	Value
Return after Costs [% p.a.]	13.60
Sharpe	0.83
Maximum Drawdown [%]	50.05
Avg Drawdown Duration [days]	37.14
Max Drawdown Duration [days]	1431
Monthly Skew	0.16
Lower Tail	1.44
Upper Tail	1.31
Winning Days [%]	52.87
99% Historical VaR [%]	87.54

Table 2: Performance statistics of cross-sectional momentum strategies with mixed lookback

So where is the benefit of diversification?

Above comparison was made to show you how dangerous it is to compare anything against some data mined best strategy. The correct comparison is to compare the average Sharpe ratio of our parameter range (0.72) to the parameter mix within this range (0.83).

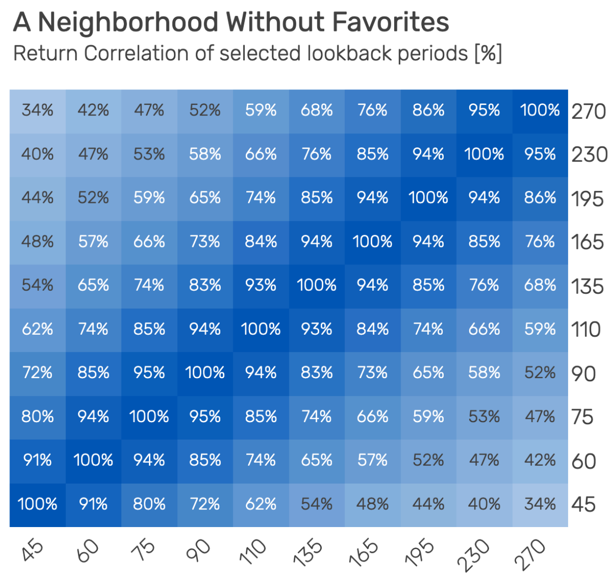

Figure 7: Correlations between cross-sectional strategy returns with a mix of lookback periods.

The correlations of the selected parameters are shown in figure 7. The Sharpe ratio increase of 0.1 corresponds to an improvement of 15%. As can be seen from figure 1, such an improvement can be expected from a combination of return streams that are correlated by 44%. All in all, not bad!

Of course you may argue that such comparisons are not very helpful, because the strategies also have different expected returns, which also play a role in the Sharpe ratio. Diversification in practice is a much more messy concept than in theory.

Nevertheless, the central idea survives contact with reality. Diversifying across carefully selected parameterizations does not create miracles, but it reduces dependence on any single choice.

Instead of betting everything on one lookback period, we allow several reasonable variants to work together. In systematic trading, that is often the closest thing to a free lunch that actually exists.