CHAPTER 11

What the Professionals Have Done

In this chapter we examine those common denominators, in terms of portfolio and systems management, that seem to be shared among the more successful commodities funds.

In looking at the real world now, versus the theoretical one in which we have been mired thus far in the text, we will now consider those fund managers regarded as the long-term trend followers, and not some of the more novelty acts.

We're looking at the *successful long-term trend followers* here. That is, we are focusing on those who manage the most money in the CTA business, have for a number of years, and, over those years, have had considerable success both in the markets with these funds as well as raising investment money in the funds. These are all quite recognizable names as of this writing.

Why pick them? First, they manage the largest amounts that are invested in futures speculation. In fact, I would venture to say that as of this writing, and for decades preceding it, well over half of the money in managed futures has been under the control of what might be termed *long-term trend following*.

Second, the larger investors—that is, the institutions that now allocate a small portion of their enormous funds to futures and alternative-type investments—have been attracted by these funds. Therefore, from a business standpoint, the funds have been unquestionably successful, and it is exactly that type of success that so many fund managers covet.

Lastly, exactly because there *is* this enormous chasm between what these successful funds and individuals do, versus the optimal *f*/Leverage Space Model framework, as discussed to this point, it bears discussion.

Here are the main, common tactics that most of these successful long-term trend-following funds are following:

COMMONALITIES

1. Most everyone is risking x percent per trade on a given market system. Typically, this is in the neighborhood of 0 to 2 % per trade. This risk is essentially determined by where the stop out is on the given trade, and the money at risk in the account. Thus, if the risk is 1% per trade, and there is $10 million in the account, the percentage of risk on the trade is $100,000. If the stop-out point on this trade was $1,000 from the entry, there would be 100 contracts put on.
2. The stop-out points are almost always a function of recent volatility in one fashion or another—often, the stop-out being a multiplier of the previous X bar's average range (times something, usually a constant value like 3) , or something along the lines of "the lowest low in the past X bars" (which, too, is a function of recent volatility). There is always seemingly a *recent volatility* metric that is employed in the quantity calculation. Thus, the more volatile the market, the less the quantity traded will come out to be, and vice versa.
3. Trend-following funds have typically shown virtually no concern for correlation, though stock traders do. In other words, a manager who trades, among other things, dollar yen, sterling, and dollar euro may have a 1% position concurrently in all three markets, lined up on the same side of the dollar, while at other times will have only one such position on, for a net risk of 1% versus the dollar. This is not at all uncommon to see in the real world of successful fund managers, the rationale being that if, say, in this example, all three are making a good run, and you are trading all three as separate market systems, then that dictates you should take this 3% risk versus the dollar at this time.

Of course, if you were risking 20% per position, you might not follow this rule and have 60% of the equity on the line against the dollar! The luxury of being able to nearly disregard correlation is a function of not being anywhere near what would otherwise be the optimal f on these positions. Again, this is a major divergence between theory and practice.

DIFFERENCES

The main differences between these funds, then, aside from where their stops are, is the markets they trade (this is the biggest difference between most of them). Essentially, long-term trend-following systems will be long a raging bull market in whatever tradable you're looking at. However, the major differences are the stops. The different philosophies are:

1. Always in a market. This is a two-phase approach ("long/short") versus a three-phase ("long/flat/short") approach. Often, these two approaches are combined and netted out. However, a two-phase approach in a long-term trend-following system will typically have stops much farther away than a three-phase system. Since the distance the stop is away from the market will dictate the quantity, very often the two-phased types of systems will have on considerably less quantity.
2. Markets traded. Typically, most managers of the successful long-term trend-following systems (I'm speaking of the larger fund managers here) trade about 20 markets, give or take half a dozen. These typically are the markets that are liquid enough to facilitate the quantity they are trading in. This is where a lot of guys are fooling themselves by selecting a handful of lucky markets. However, though they may trade client money in only those markets, they will often trade their own money in ALL markets.

Some managers *do* trade all markets—rough rice, rapeseed, etc.—with the thought that there are going to be giant trends somewhere, and the only way to participate in them is to be in those markets.

Of course, there are the novelty acts that trade only grains or only currencies, for example, but these are of no real interest to us in this discussion.

FURTHER CHARACTERISTICS OF LONG-TERM TREND FOLLOWERS

There is also the decision of how frequently the size of a position is altered. The answer to this could have fallen under either the "Commonalities" section or the "Differences" section.

Typically, when you speak with these fund managers, they will almost unanimously tell you that if there were no costs to doing so, they would alter their position sizes as frequently as possible—in fact, if it were possible, they would adjust them continuously. This is indicative of someone practicing portfolio insurance of some sort—that is, replicating an option, where their size is the option's delta percent of what it would be if it were very profitable (i.e., the systems equity curve were deep in the money). In other words, they replicate an option on that market system's equity curve.

Yet, in application, managers differ wildly from this. One of the most successful (who always has a position in a given market) will alter his size only on every rollover occurrence.

There is also the practice of staggering entries and exits. That is, most of these funds are so large that if they are required to execute a trade at a particular price, rather than moving the market in a big way at that particular price, they may break up that sizable order into numerous smaller orders and execute them at various prices near the price that was supposed to be the actual order price. Some fund managers practice this; others do not. Surprisingly, the deciding factor does not seem to be a function of the size of the fund! Some funds will throw an enormous order at a single, given price.

This same notion of staggered entries and exits is sometimes practiced in the context of multiple systems on the same market. As a simplified example, suppose I am a fund manager and I have a system that has a single parameter, and that system for today calls for me to enter a particular market at a price of 100.

Rather than operate in this fashion, it is often common to have different parameters, in effect creating different "systems," as it were, causing a staggering of entries and exits. This is a fairly easy process.

So, whereas intentional staggering of entries and exits to mitigate slippage is not universally employed, the notion of inadvertently doing this, or staggering entries and exits as a fortunate by-product of using numerous parameters on the same market system, is quite pervasive and accepted.

The concept of using an array of parameter values is also rather widely thought to help alleviate the problems of what parameter values to use in the future, based on historical testing. The thinking is that it is difficult to try to pinpoint what the very best parameter will be in the future. Since most of these systems are *robust* in terms of giving some level of positive performance against a wide spectrum of parameter values, by using an array of parameter values, fund managers hope to avoid selecting what in the future will be an outlier parameter value in terms of poor return. By using an array of parameter values, they tend to come in more toward what the typical parameter performance was in the past—which is acceptable performance.

Parameter optimization tends to be fraught with lots of questions at all levels. Though the concept of parameter optimization is, in effect, inescapable in this business, my experience as an observer here is that there is not much to it. Essentially, most people optimize over the entire data set they can get their hands on, and look at the results for parameter values over this period with an eye toward *robustness* and trying to pick that parameter value that, though not necessarily the peak one, is the one in a range of parameter values where all have performed reasonably well. Additionally, they tend to break down the long history of these runs into thirds, sometimes fourths. For example, if they have a 28-year history, they will look at things in 7-year increments—again, with the same criteria. Of note here is the question of whether they use the same parameter values from one market to another. Typically, they do not, using a different set of parameter values for different markets, though this is not universal.

Additionally, as for how frequently they optimize and reestablish parameters, this too seems to be all over the board. Some do so annually, some do it considerably more frequently than that. Ultimately, this divergence in operations also seems to have little effect on performance or correlation with one another.

There has been a trend in recent years to capture the characteristics of each individual market's prices, then use those characteristics to generate new, fictitious data for these markets based on those characteristics. This is an area that seems to hold great promise.

The notion of adding to a winning position, or *pyramiding*, is almost completely unseen among the larger fund managers. That is, there just don't seem to be any large funds out there that add to winning positions according to some schedule as a trade progresses. However, this is occluded, as many funds that employ multiple trend-following systems and/or an array of parameter values for a given market system will inadvertently add to positions. Aside from that, the concept of pyramiding is virtually unseen.

Almost as rare is the notion of taking profits. Rarely do any of these funds have a set target where they will exit a trade. Rather, there is almost always a trailing stop, whereby the position is either exited or flipped.[1]

Related to the notion of exiting a trade at a specified target is the entire concept of trying to smooth out the equity curve. These techniques have been employed with varying and, in most cases, none-too-stellar success.

Attempts to do this are often along the lines of so-called *anti-trending systems*, that is, systems that tend to profit in flat markets. Again, since these successful funds profit when there are trends, they tend to suffer in the absence of such trends. Hence the emergence of anti-trending systems along the lines of option writing (covered or uncovered, often with spreads of the butterfly type—essentially anything that takes premium at the establishment of the position), or convertible-type arbitrage, etc. (The list of anti-trending types of systems is nearly endless and unbelievably creative! There is a long list of anti-trending types of systems devised in recent years.)

[1]There are individual traders, however, who have had great success with taking profits on trades and are far more short-term oriented, particularly those of the bailout-type exits. The reason for this is that by being able to convert many losing trades—as well as diminishing what otherwise might be large winning trades, to effectively a scratch, the standard deviation in returns from trade to trade is tightened up. Per the Pythagorean Theorem, from previous chapters, this is effectively the same as increasing the arithmetic average trade in terms of growth on an account.

Ideally, managers would like to have trend-following systems that are uncorrelated or even perhaps negatively correlated. However, these don't seem to exist, and, quite likely if something was spotted that exhibited this characteristic, in the absence of a causal factor for the correlation, it might well be ready to turn and perform in an opposite manner.

The idea of trading anti-trending systems has been to both mitigate drawdown by attempting to smooth out the equity curve and to provide a somewhat regular return on a fund, an attempt to give a certain *buoyancy* to its performance.[2] There has been a prevailing trend in the industry that the only way you can interest the larger institutions to invest with you is if you can produce 1 to 1.5% returns per month with limited drawdowns. Fund managers have attempted to incorporate these convergent, anti-trending types of systems into the process with that goal in mind. Ultimately, however, very little (aside from the increase in automation) has changed in the way successful funds operate in terms of their market strategies. Attempts to incorporate convergent, or anti-trending, systems have shown limited success thus far.

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In 1984, a group of well-trained and highly screened individuals, who were at the time nontraders, and who were subsequently dubbed the *Turtles*, laid out a lot of these basic commonalities regarding successful long-term trading when they began opening up about their training. This was the group Richard Dennis founded in a dispute with his colleague William Eckhardt over whether successful trading skills could be taught.

Since that time, supposedly, some of the original Turtles have seen great success; others, failure. The distinguishing characteristics, though speculated upon by many, aren't really known (by me anyhow). However, it should be mentioned at this point that failure, usually in a system that, in the long run, shows a profit, is solely the result of where one stops in the equity cycle. Clearly, even at a very modest level for f, the drawdowns to be expected are extreme. In a system that will, say, at the end of five years, be wildly profitable, very likely that system has had some hair-curling, greater-than-anticipated drawdowns. Quitting in such a drawdown, then, is considered failure.

[2]As of this writing, interest rates of any duration are and have been near their lows of four decades. In addition to protracted, multiyear drawdowns that many of these funds are experiencing as of this writing, the low interest rates seem to have created an atmosphere that may have promoted the idea of further incorporating anti-trending types of systems.

Put another way, if you own a casino, and an individual comes in, has a few plays that break in his favor, and you quit the casino business at that point, having lost money at it for the duration of being in the casino business, then, yes, you are, by definition, a failure in the casino business.

As of this writing, February 2006, the long-term trend followers are in the midst of a protracted multiyear drawdown, with many funds down well over 50%. People are saying, "Long-term trend following is dead."

As you will see in the next chapter, "The Leverage Space Portfolio Model in the Real World," this type of drawdown is absolutely expected and normal. In fact, it may well get worse before it gets any better.

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Given these basic building blocks of allocation, however seemingly crude, one could (and many, in fact, have) create successful commodity funds. Merely by risking 1% of an account's capital on 20 seemingly disparate markets (or not so disparate, even, given how few markets are available for some funds because of their liquidity constraints as dictated by their size), some funds have seen wild success over the years by any measure; and, peculiarly, with no concern for correlations.[3]

One very large, very successful fund that has been around for a generation has operated that very way since inception and is known for coming through with nice returns over time, with rather small, perfectly digestible-to-most drawdowns. Another long-term, successful fund with roughly USD 1 billion currently trades only about a dozen markets with a single model and three parameter sets per market.

By contrast, one of their close competitors with a similar amount under management, and funds highly correlated to the one just mentioned, use six to eight models with dozens of parameter sets for each market and a basket of over 60 markets! As would be expected, their returns have historically been smoother, but not relatively to the extent one might expect.

With the majority of the commodity funds, however, that 20% figure could be 5% or it could be 50%, but at 20% you'll be right in the mainstream, right in or near the fattest part of the curve. As for the stop-out amount, typically this would be the lesser of 2% of an account's equity or the percentage allocated to trading (again, 20% putting you in the fat part of the curve), divided by the number of markets traded.

[3]This may not be such a bad approach. Given that correlations do not seem to maintain consistency with the magnitude of swings, when all cut against you, in such an allocation model, you are looking at a 20 % loss.

Does this mean that mean-variance models are not employed? Though a gross generalization, in terms of the individual funds, it most often is not. However, with the larger pools and fund of funds, it tends to be. So the general rule out there seems to be that if it is a solitary fund, a single market system, say, across markets, mean-variance is not employed most of the time, whereas, if it is a conglomeration of funds—or market systems, it tends to be used more.

This is not to say that individual funds are not looking to pair uncorrelated items together, or are not working to smooth out their equity curves via a mean-variance approach. However, and particularly more recently, the individual large funds appear to be looking more toward a *value-at-risk* means of allocation, and more toward the notion of trying to get the biggest bang they can out of their funds within the constraint of "acceptable" drawdowns.

Sometimes, they are looking at individual markets and their individual drawdowns, then the drawdowns of the portfolio as a whole. Most larger funds appear to allocate an equal amount of risk to each market and then scale the whole portfolio up to the acceptable level of risk to see what the return is.

Still others do each market individually, so in the markets that have performed better, the percentage of equity to risk on each trade in an attempt to achieve an x percent chance of a y percent drawdown is higher. Then these different percentages for each market are tested together, obtaining a single portfolio, which is then further scaled up or down to retain that x percent chance of a y percent drawdown for the entire portfolio. Note that under this method, a market that was twice as profitable will end up getting twice as much allocated to it.

The interesting aspect of this approach (versus merely allocating an equal amount of risk to each market, then scaling the portfolio up or down as a whole to achieve the desired risk level)—that is, of preprocessing by each individual market, thus, when you subsequently scale the whole portfolio, achieving different allocations to different market systems—is, in effect, you have employed mean variance indirectly. Thus, such an approach can be said to combine mean variance with value at risk.

This type of an approach is typically employed in the following manner. Let's suppose you have 25 years of historical data. For each market, then, you look through all the data, seeking to obtain that percentage of equity to risk in each market such that there are no more than $25 \times 12 = 300$ months $\times$ $1\% = 3$ months, where the loss was greater than 20%. This is typically regarded as the standard way to obtain value at risk from a trading study. Once you have obtained this percentage of equity to risk for this particular market system, you must decide if the return over that period justifies including it in the portfolio.

Once you have settled on the components of the portfolio and their relative percentages of risk, you then perform step 2, which is to look at the portfolio as a whole, to determine a scaling factor by which to multiply all the component risk percentages. Funds that allocate a same risk level to each market system perform only step 2 of this analysis.

In implementation, before a trade is to be initiated, the stop on the trade on a per-contract basis is determined. Now, the portfolio value (some use the current value; some, the value as of last night; others, the value at the beginning of the month) is divided by the portfolio scaling factor adjusted risk percentage for this market, and that number is then divided by the risk per contract on this trade, to determine the number of contracts to allocate.

So, if we have a $1 million account, and our stop-out on a one-contract basis on this trade is $5,000, the relative percentage of risk is 4% (the number that gave us no more than an x percent chance of a y percent drawdown over the 25 years of past data for this market), and our portfolio scaling factor is .7 (the number that gave us no more than an x percent chance of a y percent drawdown over the 25 years of past data for the portfolio as a whole). We then have:

$$1{,}000{,}000 \times .04 \times .7/5{,}000 = 5.6 \text{ contracts}$$

Note the .04 here, for most funds, is typically a constant from one market system to the next, but again, there are some funds that do derive this number individually for each market system.

Of note here too is the .7 portfolio scaling factor. If all markets were perfectly correlated, then this number would equal 1 divided by the number of market systems in the portfolio. Therefore, the higher you can get this number, the less correlated the constituent market systems are. If you had only two components and there was a negative correlation, your portfolio scaling factor would actually be greater than 1.

However, it may not be a bad bet to expect worst months among market systems to cluster together in the future, and therefore, may *not* be a bad bet to simply say that your portfolio scaling factor is to be 1 divided by the number of market systems in the portfolio.

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These concepts aren't altogether complicated as applied in the crude ways they are being employed in the real world as outlined here. What is hard is getting software that can do this, keep track of the equity, perform the rollovers for the raw futures data rather than continuous contracts, and so on. The concepts as expressed here are actually pretty easy, but getting the tools to do it accurately is not.

Furthermore, as we are yet to see in this text, the way detailed here is far from an accurate assessment of what these fund managers are seeking to discern. The techniques shown in this chapter will give an overly optimistic assessment of the potential risk.

We've gone into greater detail here than what we really were looking for, that is the disparity between optimal *f*/ Leverage Space Model framework and what these successful and long-standing funds do. However, we also see that they are trying to fit a mean-variance approach and a value-at-risk approach to meet the dictates placed upon managed futures of a utility preference curve that is anything but ln.

Chapter 8 explored the relationship between mean variance and optimal *f*. In Chapter 12, we will show how the notions of mean variance, value at risk, and the Leverage Space Model are interrelated, and how, in fact, they all work together to achieve what the fund manager seeks. It is precisely this process that is the focus of the final chapter.