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Two benchmarks for momentum trading

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Returns in the CTA sector probably can be best understood as the combination of two powerful forces. One is the influence of trend following or momentum trading, which appears over long stretches of time to be profitable. The other is the presence of uncorrelated trading strategies that are also profitable and whose diversifying effects greatly improve the risk/return profiles both of individual CTAs and of portfolios of CTAs.

The influence of trend following on CTA returns can be seen clearly in Exhibit 1, which shows two relationships. In the upper panel is the relationship between weekly returns of the Newedge CTA Index, which comprises roughly equal numbers of trend followers and non-trend followers, and the newly minted *Newedge CTA Trend Sub-Index*, which captures the returns of a subset of CTAs who are widely recognized in the industry as trend followers. Here we see that the relationship is tight and that the overall correlation of returns for 2000 through 2009 was 0.97.

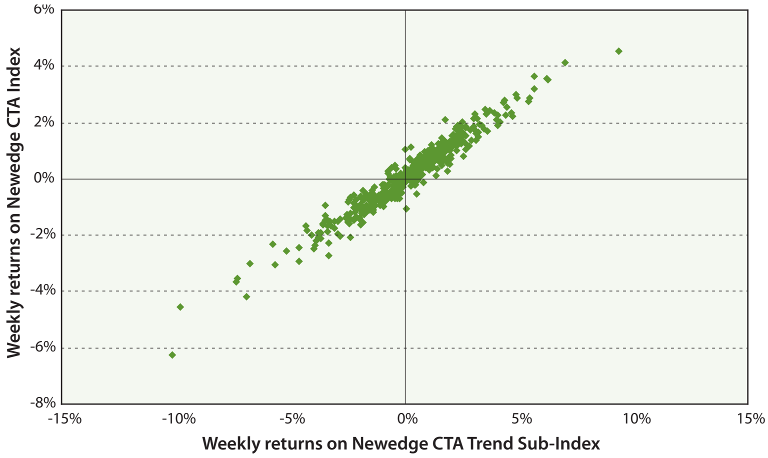
In the lower panel is the relationship between weekly returns on the Newedge CTA Trend Sub-Index and those on a basic 20/120 moving average model that employs a broadly diversified, volatility weighted portfolio of futures on equities, interest rates, foreign exchange and commodities. In this case, the correlation was 0.67, which is a value that looks like the correlations that the subset of trend followers' returns exhibit with one another.

Given its comparatively high and stable correlation with actual trend following CTAs, we believe that this particular trend following model and parameter combination – which we will publish as the *Newedge Trend Indicator* – has a useful role to play for both investors and managers. Investors will have a benchmark that provides position level transparency in all of the markets that it employs, which in turn allows ready access to information about sources of returns. For their part, managers will have an independent, no-ax-to-grind, standard of comparison that they can use in conversations with their clients.

Exhibit 1

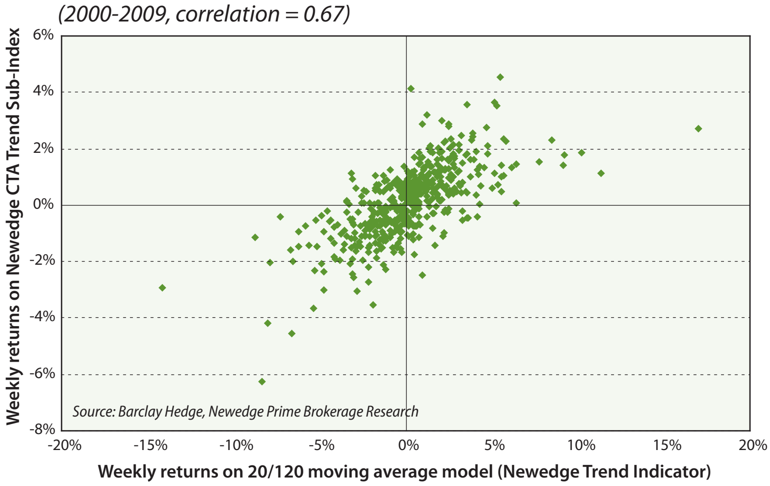
Correlation between Newedge CTA Index and Newedge CTA Trend Sub-Index

(2000-2009, correlation = 0.97)



Correlation between Newedge CTA Trend Sub-Index and 20/120 moving average model (Newedge Trend Indicator)

(2000-2009, correlation = 0.67)



Source: Barclay Hedge, Newedge Prime Brokerage Research

Both of these new benchmarks will be published daily. The main purpose of this note is to describe the construction of the two benchmarks, especially the work involved in building even the most basic trend following models. These include:

- Our choices of markets to trade
- The creation of continuous futures price series
- The treatment of trade execution and transaction costs
- Our choices of position weights to create balanced, volatility weighted portfolios, and
- Our choice of the 20/120 moving average model

We also review the lessons we learned along the way, including

- The high and stable correlation that can be achieved with the simplest moving average model
- The importance of liquidity and transaction costs in building portfolios and managing contract rolls
- The challenges to managing return volatility, and
- Where and when trend following models made money during the years 2000 through 2009

The data and the trend following sub-index

In *What you should expect from trend following*, which we published in 2004, we worked with a 10-year period from 1994 through 2003. In this round of work, we focus instead on the 10-year period from 2000 through 2009, which allows us to work with the behavior of the Newedge CTA Index, which was first published in January 2000.

The Newedge CTA Index

The Newedge CTA Index is nearly ideal for a case study on trend following. First, it represents the largest CTAs that were open for investment, and so we are looking at a realistic portfolio for large, institutional investors. Second, while the relative representation of trend followers in the index has varied slightly from year to year, the average number of trend following CTAs in the index was roughly half. Third, we have daily return data, which allow us to focus almost as finely as we want on what drives CTAs' returns. Fourth, we know all of the constituents well and are able to identify easily and reliably those CTAs that have generally been recognized in the industry to be trend followers.

Exhibit 2
Trend followers in the Newedge CTA Index

	Trend followers	Non-trend followers	Total	Trend following share
2000	10	8	18	0.56
2001	9	10	19	0.47
2002	7	10	17	0.41
2003	11	11	22	0.50
2004	10	12	22	0.45
2005	10	13	23	0.43
2006	9	6	15	0.60
2007	9	11	20	0.45
2008	10	10	20	0.50
2009	11	9	20	0.55
	96	100	196	0.49

Source: Barclay Hedge, Newedge Prime Brokerage Research

The Newedge CTA Trend Sub-Index

For the purposes of this research, we constructed an index based on the performance of those CTAs who were generally known to be trend followers. For each of the years, the selection process included two steps. The first was to select by name the CTAs who were known to be trend followers. A head count of trend followers and non-trend followers in the Newedge CTA Index is shown by year in Exhibit 2. On average over the full ten years, trend followers accounted for just under half of the CTAs in the broader index, although their relative importance was as low as 41% in 2002 and as high as 60% in 2006.

The second was a reasonableness check that involved a correlation cluster analysis to see if their return correlations supported the idea that they shared something in the way they traded. An example of such a correlation cluster analysis is provided in Exhibit 3, which shows the results for 2009. In this analysis, all CTAs in a cluster must have a minimum correlation of 0.50 with every other CTA in that cluster. As it turned out, the trend followers fell into two fairly highly correlated groups, while most of the rest formed groups of one, or at most two. The one exception in this example was IKOS Partners, which fell into the larger correlation cluster of trend followers even though IKOS does not represent itself as a trend following manager.

Three correlation questions

This new index, which will be published as the Newedge CTA Trend Sub-Index, is calculated the same way as the Newedge CTA Index. That is, it assigns equal weight to each CTA at the time it is reconsti-

Exhibit 3

Correlation cluster results of daily returns for CTAs in the 2009 Newedge CTA Index

Designation		CTA	Correlation																			
			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
TF	1	Altis Partners (GFP Composite)	1.00	0.72	0.78	0.78	0.70	0.54	0.74	0.66	0.72	0.63	0.71	0.60	0.08	0.10	0.45	0.27	0.16	0.18	0.24	0.21
TF	2	Campbell & Co., Inc. (FME Large)	0.72	1.00	0.82	0.81	0.67	0.67	0.70	0.50	0.62	0.49	0.75	0.63	-0.01	0.05	0.33	0.30	0.36	0.25	0.06	0.21
TF	3	Graham Capital (Diversified)	0.78	0.82	1.00	1.00	0.69	0.79	0.75	0.43	0.55	0.49	0.59	0.48	-0.01	0.01	0.42	0.20	0.20	0.09	0.12	0.14
TF	4	Graham Capital (K4)	0.78	0.81	1.00	1.00	0.69	0.79	0.74	0.43	0.55	0.49	0.58	0.48	-0.01	0.00	0.42	0.20	0.20	0.09	0.12	0.14
	5	IKOS Partners (Financial USD)	0.70	0.67	0.69	0.69	1.00	0.55	0.56	0.38	0.58	0.34	0.55	0.53	-0.14	-0.01	0.34	0.23	0.15	0.14	0.22	0.29
TF	6	Sunrise Capital (Diversified)	0.54	0.67	0.79	0.79	0.55	1.00	0.68	0.14	0.36	0.50	0.44	0.37	-0.09	-0.19	0.27	0.20	0.13	0.06	-0.17	0.15
TF	7	Transtrend, B.V. (Admiralty Fund)	0.74	0.70	0.75	0.74	0.56	0.68	1.00	0.53	0.64	0.53	0.66	0.60	0.19	0.16	0.46	0.17	0.31	0.16	0.21	0.23
TF	8	Aspect Capital (Diversified)	0.66	0.50	0.43	0.43	0.38	0.14	0.53	1.00	0.79	0.61	0.80	0.77	0.25	0.23	0.34	0.36	0.34	0.21	0.51	0.27
TF	9	Brummer & Partners (Lynx)	0.72	0.62	0.55	0.55	0.58	0.36	0.64	0.79	1.00	0.65	0.78	0.77	0.22	0.25	0.43	0.30	0.38	0.27	0.31	0.50
TF	10	Chesapeake Capital (Diversified)	0.63	0.49	0.49	0.49	0.34	0.50	0.53	0.61	0.65	1.00	0.71	0.71	0.26	0.07	0.37	0.37	0.27	0.27	-0.04	0.32
TF	11	Millburn Ridgefield (Diversified)	0.71	0.75	0.59	0.58	0.55	0.44	0.66	0.80	0.78	0.71	1.00	0.86	0.23	0.17	0.40	0.46	0.41	0.25	0.18	0.36
TF	12	Winton Capital (Diversified)	0.60	0.63	0.48	0.48	0.53	0.37	0.60	0.77	0.77	0.71	0.86	1.00	0.22	0.15	0.41	0.53	0.41	0.30	0.25	0.31
	13	Crabel Capital (Multi-Product)	0.08	-0.01	-0.01	-0.01	-0.14	-0.09	0.19	0.25	0.22	0.26	0.23	0.22	1.00	0.68	0.51	0.18	0.36	0.08	0.09	0.30
	14	R.G. Niederhoffer (Diversified)	0.10	0.05	0.01	0.00	-0.01	-0.19	0.16	0.23	0.25	0.07	0.17	0.15	0.68	1.00	0.48	0.16	0.34	0.18	0.22	0.23
	15	QIM (Global)	0.45	0.33	0.42	0.42	0.34	0.27	0.46	0.34	0.43	0.37	0.40	0.41	0.51	0.48	1.00	0.24	0.18	0.12	0.13	0.32
	16	Grossman Asset Mgmt. (Currency)	0.27	0.30	0.20	0.20	0.23	0.20	0.17	0.36	0.30	0.37	0.46	0.53	0.18	0.16	0.24	1.00	0.20	0.18	0.09	-0.09
	17	FX Concepts (Global Currency)	0.16	0.36	0.20	0.20	0.15	0.13	0.31	0.34	0.38	0.27	0.41	0.41	0.36	0.34	0.18	0.20	1.00	0.44	0.14	0.32
	18	FX Concepts (Dev. Market Curr.)	0.18	0.25	0.09	0.09	0.14	0.06	0.16	0.21	0.27	0.27	0.25	0.30	0.08	0.18	0.12	0.18	0.44	1.00	0.04	0.22
	19	Eagle Trading Systems (Yield)	0.24	0.06	0.12	0.12	0.22	-0.17	0.21	0.51	0.31	-0.04	0.18	0.25	0.09	0.22	0.13	0.09	0.14	0.04	1.00	-0.03
	20	Boronia Capital (Diversified)	0.21	0.21	0.14	0.14	0.29	0.15	0.23	0.27	0.50	0.32	0.36	0.31	0.30	0.23	0.32	-0.09	0.32	0.22	-0.03	1.00

Source: Barclay Hedge, Newedge Prime Brokerage Research

tuted, which is the first business day of the year.

While we do not want to get sidetracked by anything that is not directly related to developing benchmarks for trend followers, we have in the course of our work encountered three questions about correlation that we think deserve attention. These are:

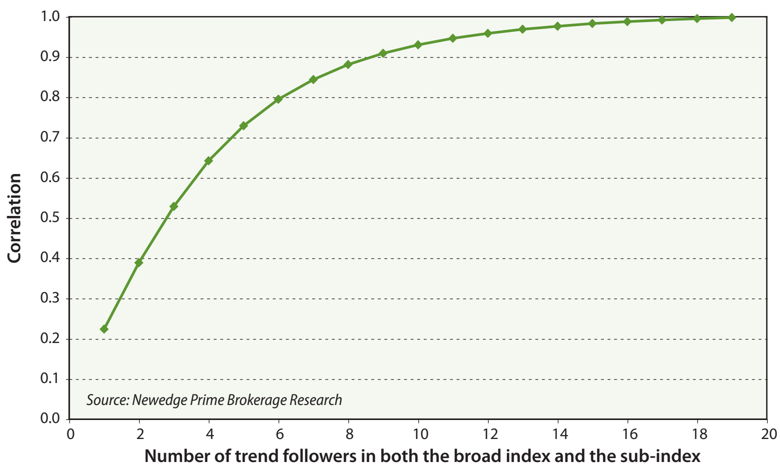
- How is it possible for the correlation between returns on the Newedge CTA Trend Sub-Index and those on the broader Newedge CTA Index to be as high as they are when the pair-wise correlations we observe are substantially lower?
- How hard is it to build a CTA portfolio whose returns are not highly correlated to a pure trend following CTA portfolio?
- How is it that IKOS, which is not principally a trend following CTA, appears in a large correlation cluster with a group of well known trend followers?

Although we intend to deal with these questions in a separate research note, we think the key to all three questions is in the averaging of returns that one does when building an index or a portfolio.

Exhibit 4

Correlation between returns on a sub-index of correlated returns and a broader index

(Correlation among "trend followers" = 0.60, all other correlations = 0.0, total number of CTAs = 20)



Consider, for example, Exhibit 4, which shows how the correlation between returns on two indexes – a broad index that contains both correlated and uncorrelated assets and a sub-index that contains only the correlated assets – changes as the number of correlated assets in the mix increases. To construct this exhibit, we assumed that return volatility was the same for all CTAs, that the correlation of trend followers' returns with other trend followers' returns was 0.6, and that all other return correlations – trend followers with non-trend followers and non-trend followers with one another – were zero. Measured along the horizontal axis is the number of trend followers in both the broader index and the trend following sub-index. For this exercise, the total number of CTAs was set at 20.

What stands out in this exhibit is just how quickly the presence of correlated returns in a broader index influences the relationship between the two. With only one or two trend followers in the broader index, the correlation of returns between the two is fairly low. But once the number of trend followers

Exhibit 5

How much will a portfolio resemble trend following?

(Correlation between portfolio returns and returns on a 10-asset trend following sub-index)

($\rho_{TF} = 0.64$, $\rho_{NTF} = .00$, $\rho_{TF/NTF} = .00$)

# of trend followers in portfolio	Number of non-trend followers in portfolio										
	0	1	2	3	4	5	6	7	8	9	10
0		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1	0.82	0.58	0.47	0.41	0.37	0.34	0.31	0.29	0.27	0.26	0.25
2	0.91	0.79	0.72	0.66	0.61	0.57	0.54	0.51	0.49	0.47	0.45
3	0.94	0.88	0.83	0.79	0.75	0.72	0.69	0.66	0.64	0.62	0.60
4	0.96	0.92	0.89	0.86	0.83	0.81	0.78	0.76	0.74	0.72	0.71
5	0.97	0.95	0.92	0.90	0.88	0.86	0.84	0.83	0.81	0.79	0.78
6	0.98	0.96	0.95	0.93	0.91	0.90	0.88	0.87	0.86	0.84	0.83
7	0.99	0.97	0.96	0.95	0.94	0.92	0.91	0.90	0.89	0.88	0.87
8	0.99	0.98	0.97	0.96	0.95	0.94	0.93	0.92	0.91	0.90	0.90
9	1.00	0.99	0.98	0.97	0.96	0.95	0.95	0.94	0.93	0.92	0.92
10	1.00	0.99	0.99	0.98	0.97	0.96	0.96	0.95	0.95	0.94	0.93

($\rho_{TF} = 0.64$, $\rho_{NTF} = .21$, $\rho_{TF/NTF} = .27$)

# of trend followers in portfolio	Number of non-trend followers in portfolio										
	0	1	2	3	4	5	6	7	8	9	10
0		0.33	0.42	0.48	0.51	0.54	0.56	0.58	0.59	0.60	0.61
1	0.82	0.72	0.70	0.69	0.69	0.69	0.69	0.69	0.69	0.69	0.69
2	0.91	0.85	0.82	0.80	0.79	0.78	0.77	0.76	0.76	0.75	0.75
3	0.94	0.91	0.88	0.86	0.85	0.84	0.83	0.82	0.81	0.80	0.80
4	0.96	0.94	0.92	0.90	0.89	0.88	0.87	0.86	0.85	0.84	0.83
5	0.97	0.96	0.94	0.93	0.92	0.90	0.89	0.88	0.88	0.87	0.86
6	0.98	0.97	0.96	0.95	0.93	0.92	0.91	0.91	0.90	0.89	0.88
7	0.99	0.98	0.97	0.96	0.95	0.94	0.93	0.92	0.92	0.91	0.90
8	0.99	0.98	0.98	0.97	0.96	0.95	0.94	0.94	0.93	0.92	0.92
9	1.00	0.99	0.98	0.98	0.97	0.96	0.95	0.95	0.94	0.93	0.93
10	1.00	0.99	0.99	0.98	0.97	0.97	0.96	0.96	0.95	0.94	0.94

Source: Newedge Prime Brokerage Research

makes up half of the total, the correlation between the sub-index returns and the broader index returns exceeds 0.90. So the value of 0.97 that we see in the upper panel of Exhibit 1 makes sense.

As for the second question, the information provided in Exhibit 5 suggests that it is extraordinarily difficult to build a portfolio whose returns don't look like trend following returns, even under the best of circumstances. In the upper panel, we have assumed that the average pair-wise correlation of trend followers' returns is 0.64, and that all other correlation pairs are zero. In such a world, if one had as few as three trend following CTAs, it would be difficult to reduce the portfolio's return correlation with the trend following sub-index to less than 0.60.

But if we use correlations more like those we observe in practice, the task becomes nearly impossible. The correlation values we used in the lower panel are the average values we observed for 2009. Using these values, we find the fairly shocking result that a portfolio with no trend followers at all can produce returns with a correlation of 0.60 to those on the trend following sub-index. And if the portfolio has just one trend follower, it would be impossible to reduce the portfolio's return correlation to anything less than 0.69.

With regard to the presence of IKOS in a cluster of well known trend followers, what we may be seeing at the individual CTA level is the influence that trend following can exhibit on one's return correlations, even if it represents a small part of one's overall portfolio of trading strategies.

Exhibit 6

Net asset values for Newedge CTA Index and Newedge CTA Trend Sub-Index

(net of fees)

Ten years of net asset values

To complete the case for our interest in trend following, we have charted in Exhibit 6 the net asset values for the Newedge CTA Index and the Newedge CTA Trend Sub-Index from 2000 through 2009. Here, the eye can confirm what the scatter plots and correlation clusters suggest. That is, trend following is a major force in this industry. The fortunes of trend followers and the industry tend to rise and fall together, although with one significant difference. While the two paths follow one another closely, the total index path exhibits much lower volatility than that exhibited by the trend following sub-index path. The lower volatility stems from the presence of low correlation returns, and the result is a higher return/risk ratio for the industry than for the trend followers by themselves.

Trend following models

As in *What you should expect from trend following,* we focus on two of the most widely recognized approaches to trend following – range breakout and moving average crossover. These are extremely simple approaches to identifying trends and we apply them in the simplest possible way.

Range breakout

The simplest range breakout approach uses a single parameter, which measures the length of the look-back period for calculating high and low prices. For example, a 20-day breakout model works this way. If you are short and the price rises above the 20-day high, you reverse position and go long. If you are long and the price falls below the 20-day low, you reverse position and go short. In the work that follows, we consider look back periods from 20 to 240 days.

Moving average crossover

This approach calculates two moving averages – one for a short period (the fast average or F-day average) and one for a longer period (the slow average or S-day average). In this approach, if the fast average is above the slow average, you are long. If the fast average is below the slow average, you are short. In the work that follows, we consider every combination of fast and slow day pairs involving fast days from 20 to 220 and slow days from 40 to 240.

You can find illustrations and more complete explanations of these two approaches in *What you should expect from trend following*.

Laying the groundwork for analyzing returns to trend following

The raw material for studying trend following includes markets, price histories, and a portfolio weighting scheme. In the spirit of being as true as possible to the way this might have worked in real life, we began each year by selecting the markets that would have been available at the time.

Choice of markets

Because we had decided to use a two-year look back period to estimate return volatilities when constructing our portfolios, we required any futures market we included to have two years of daily data as of the end of August of that year. The reason for this peculiar ending period is a production time line that we intend to use when publishing the benchmark. That is, we plan to gather data through the end of August of each calendar year, use the month of September to reselect markets, analyze the data, and construct the portfolio that will be used from October of the current year through September of the following year. Thus, any given calendar year's returns will reflect nine months of returns from the portfolio constructed in the current year and three months of returns from the portfolio constructed from the previous year.

As it was, we had 50 futures markets at the end of August 1997. These were used to construct the portfolio we used beginning October 1999. It was this portfolio's returns for the first nine months of 2000 that we use to compare the returns of the Newedge CTA Index and the Newedge CTA Trend Sub-Index. By the end of August 2009, we had 55 markets.

When constructing our price histories, we allowed for the replacement of one market by another. One such example is the substitution of the E-mini S&P500 contract for the "big" S&P500 contract.

We also used futures contracts for which we had good data to serve as proxies for trades that would take place elsewhere. For example, we used foreign exchange futures to represent cash market trades in foreign exchange. Currency futures typically are not large or liquid enough for larger CTAs, but the futures markets are sufficiently well tied to the spot and forward markets for their prices to be reliable proxies for the prices that govern trading in the cash market. We also used the COMEX copper contract in our work, although the major copper trading market is the London Metals Exchange.

Contract rolls

One of the single most important features of futures contracts is that they expire and must be replaced. The transaction that replaces an expiring September contract with a December contract is known as a "roll," and the way these rolls are handled by each CTA can have a substantial effect on the results of a trading program.

Although there are as many ways to achieve a roll as there are overlapping days in the two contracts' lives, what we find is that contract rolls in each market tend to be concentrated in a few days during which the "roll market" is as liquid as it is ever going to be.

For this reason, we adopted a roll rule that would tend to follow the liquidity. In particular, our rule was to roll:

- 2 business days after open interest in the deferred contract exceeds open interest in the lead or expiring contract, or;
- 3 business days before the lead contract expires, whichever happens first.

While not particularly sophisticated, this two-part rule should satisfy most reasonableness requirements. The first part would tend to keep us in the liquid part of the contract cycle, and the second part keeps us away from contract expirations.

Exhibit 7

Contract roll schedule

Instruments	Cycle											
CAC 40	F	G	H	J	K	M	N	Q	U	V	X	Z
DJIA Mini			H			M			U			Z
S&P 500 E-mini			H			M			U			Z
DAX			H			M			U			Z
Hang Seng	F	G	H	J	K	M	N	Q	U	V	X	Z
IBEX 35	F	G	H	J	K	M	N	Q	U	V	X	Z
KOSPI			H			M			U			Z
Nikkei 225			H			M			U			Z
NASDAQ 100 Mini			H			M			U			Z
Swedish OMX	F	G	H	J	K	M	N	Q	U	V	X	Z
Russell 2000 Mini			H			M			U			Z
MIB			H			M			U			Z
Euro STOXX 50			H			M			U			Z
SPI 200			H			M			U			Z
FTSE 100			H			M			U			Z
German Schatz			H			M			U			Z
US 3 Month Rate (Eurodollar)			H			M			U			Z
Euro 3 Month Rate (Euribor)			H			M			U			Z
US 5 Year			H			M			U			Z
UK 10 Year (Gilt)			H			M			U			Z
Australian 3 Month			H			M			U			Z
Japan 10 Year (JGB)			H			M			U			Z
UK Short Sterling			H			M			U			Z
German 5 Year (BOBL)			H			M			U			Z
German 10 Year (BUND)			H			M			U			Z
US 2 Year			H			M			U			Z
US 10 Year			H			M			U			Z
US 30 Year			H			M			U			Z
Australian 10 Year			H			M			U			Z
Japan 3 Month			H			M			U			Z
Australian Dollar			H			M			U			Z
British Pound			H			M			U			Z
Canadian Dollar			H			M			U			Z
Euro			H			M			U			Z
Japanese Yen			H			M			U			Z
New Zealand Dollar			H			M			U			Z
Mexican Peso			H			M			U			Z
Swiss Franc			H			M			U			Z
Soybean Oil	F		H		K		N	Q	U	V		Z
Corn			H		K		N		U			Z
Cocoa			H		K		N		U			Z
Crude Oil	F	G	H	J	K	M	N	Q	U	V	X	Z
Cotton #2			H		K		N			**V**		Z
Gold		G		J		M		Q		**V**		Z
Copper	F	G	H	J	K	M	N	Q	U	V	X	Z
Heating Oil	F	G	H	J	K	M	N	Q	U	V	X	Z
Coffee			H		K		N		U			Z
Live Cattle		G		J		M		Q		V		Z
Lean Hog		G		J	**K**	M	N	Q		V		Z
Natural Gas	F	G	H	J	K	M	N	Q	U	V	X	Z
Soybeans	F		H		K		N	Q	U		X	
Sugar #11	**F**		H		K		N			V		
Silver	**F**		H		K		N		U			Z
Wheat			H		K		N		U			Z
RBOB	F	G	H	J	K	M	N	Q	U	V	X	Z

Note: The months in green boxes are officially listed, but excluded from our study due to low activities.

Source: Bloomberg

Concatenating the price series

Before concatenating the price series to produce a continuous futures price series for each market, we found it necessary to take care of two practical matters. One was cleaning the data to get rid or repair obvious errors in the data series. The other was to rule out contracts in the expiration cycle that do not, for whatever reason, really attract any trading volume. Exhibit 7 shows the contract roll schedule for the markets included in our 2009 portfolio. Notice that most contracts follow a quarterly expiration, although four of the equity futures markets have a monthly expiration cycle.

We find the most complicated expiration cycles in the commodities markets, and it is here that we find expiration months that don't trade. In the table, these months are highlighted. Notice that "V" (which stands for October) is highlighted for Cotton #2 and Gold, "K" (May) is highlighted for Lean hogs, and "F" (January) is highlighted for Sugar#11 and Silver.

In its own way, the table in Exhibit 7 is a useful resource for those doing due diligence on CTAs because it provides an insight into where their issues with managing transaction costs might lie. Financial futures contracts typically expire only four times a year and tend to be liquid. Commodity futures, in contrast, expire with a much higher frequency and tend not to be as liquid. As a result, it is generally more difficult to control costs in commodities trading than it is in financial markets and requires

Exhibit 8

Market selection and portfolio weights (as of 10/1/2009)

Sector	#	Futures markets	Annual $ volatility per contract	Number of contracts	Annual $ volatility	Remark	Annual sector volatility ($)
Equity	1	CAC 40	18,017	875	15,764,611		
	2	DJIA Mini	15,371	828	12,727,250	CAPPED	
	3	S&P 500 E-mini	17,714	890	15,765,151		
	4	DAX	61,499	256	15,743,817		
	5	Hang Seng	54,459	290	15,793,123		
	6	IBEX 35	49,308	320	15,778,626		
	7	KOSPI	27,857	566	15,767,016		
	8	Nikkei 225	40,575	389	15,783,819		$174,495,468
	9	NASDAQ 100 Mini	10,364	1521	15,763,842		
	10	Swedish OMX	4,236	3722	15,766,304		
	11	Russell 2000 Mini	23,004	685	15,757,883		
	12	MIB	54,598	289	15,778,856		
	13	Euro STOXX 50	13,598	1159	15,760,337		
	14	SPI 200	26,397	597	15,759,200		
	15	FTSE 100	26,412	597	15,767,785		
Interest rate	16	German Schatz	3,149	6711	21,133,842		
	17	US 3 Month Rate (Eurodollar)	3,286	6432	21,133,480		
	18	Euro 3 Month Rate (Euribor)	2,524	6475	16,343,672	CAPPED	
	19	US 5 Year	7,236	2920	21,129,638		
	20	UK 10 Year (Gilt)	16,021	1319	21,131,914		
	21	Australian 3 Month	2,119	1083	2,294,895	CAPPED	
	22	Japan 10 Year (JGB)	62,838	336	21,113,416		
	23	UK Short Sterling	2,503	3435	8,598,659	CAPPED	$174,476,904
	24	German 5 Year (BOBL)	7,460	2833	21,134,303		
	25	German 10 Year (BUND)	11,612	1820	21,133,381		
	26	US 2 Year	5,746	3678	21,134,952		
	27	US 10 Year	11,123	1900	21,133,191		
	28	US 30 Year	16,889	1251	21,127,603		
	29	Australian 10 Year	10,466	1998	20,910,659	CAPPED	
	30	Japan 3 Month	554	990	548,034	CAPPED	
Foreign currency	31	Australian Dollar	17,280	1893	32,710,421		
	32	British Pound	14,296	2289	32,723,362		
	33	Canadian Dollar	13,645	2398	32,720,522		
	34	Euro	23,252	1407	32,715,734		
	35	Japanese Yen	17,675	1851	32,715,604		$174,479,868
	36	New Zealand Dollar	13,392	2443	32,717,653		
	37	Mexican Peso	6,136	5333	32,721,280		
	38	Swiss Franc	16,506	1982	32,714,393		
Commodity	39	Soybean Oil	9,368	630	5,901,539		
	40	Corn	8,874	665	5,901,016		
	41	Cocoa	9,524	358	3,409,506	CAPPED	
	42	Crude Oil	37,938	156	5,918,355		
	43	Cotton #2	10,441	553	5,773,829	CAPPED	
	44	Gold	23,029	256	5,895,316		
	45	Copper	27,595	135	3,725,336	CAPPED	
	46	Heating Oil	41,632	142	5,911,758		
	47	Coffee	15,162	389	5,897,869		$58,182,485
	48	Live Cattle	5,739	810	4,648,642	CAPPED	
	49	Lean Hog	6,785	654	4,437,250	CAPPED	
	50	Natural Gas	33,199	178	5,909,448		
	51	Soybeans	19,994	295	5,898,377		
	52	Sugar #11	5,565	1061	5,904,243		
	53	Silver	29,944	197	5,899,057		
	54	Wheat	17,478	338	5,907,530		
	55	RBOB	41,122	144	5,921,535		
					Portfolio		$300,011,348

Source: Bloomberg, Newedge Prime Brokerage Research

a higher level of knowledge about the ways those markets work.

Constructing a portfolio

In choosing the numbers of contracts to hold in each market, we had two objectives. The first was to construct a portfolio for which the standard deviation of gains and losses would translate into an annualized return volatility of 15% on a $2 billion portfolio. We chose 15% because it is roughly consistent with the return volatility we observe in the industry. We chose $2 billion because it was a large enough number to force us to think about market liquidity and feasible position sizes. Thus, our objective was an annualized standard deviation of daily gains and losses of $300,000,000.

Volatility weights

The second objective was to volatility weight our contract positions. In practice, we approached the problem by dividing the world into four broad market sectors – equities, interest rates, foreign exchange, and commodities – and assigning them relative volatility weights of 30%, 30%, 30%, and 10%. We chose a lower weight for commodities to reflect the fact that these markets are, in general, less liquid than the financial markets. A number of managers have suggested that we could increase the weight for commodities without incurring too great a liquidity burden, or that we should reduce the weight of a sector like equities. As it is, we chose these weights because they are plausible, and we plan to review our weighting methodology in the next round of research.

We did all we could to assign equal volatility to each contract within each broad sector. The major impediment to this objective was market size. We limited our positions to the smaller of 1% of average open interest or 5% of average daily volume, where these averages were calculated over the two years leading up to choice of portfolio weights. We did not constrain positions in foreign exchange markets because these are generally viewed as providing more than enough liquidity for the kinds of portfolios we were building.

Volatility estimation and forecasting

In this round of research, we use the two previous years of data to establish contract weights for the following year. Thus, we are using a two-year look back and a one-year look forward. As a forecasting method, this approach worked fairly well, at least in eight out of the ten years in the study. The longish look back period and the fairly long look forward period allow temporary changes in volatility to wash out over time. We did find, though, that such a long look back period did not work well during the financial crisis of late 2008 and early 2009. During these years, our portfolios exhibited volatility that was roughly twice what we had targeted. In contrast, we found that actual CTAs were more nimble in their risk management and succeeded in keeping their return volatilities under control.

Sample portfolio

An example of the kind of portfolio this approach produced is shown in Exhibit 8, where you can see all of the markets traded and the number of contracts used in each case. In this case, we used data from September 2007 through August 2009 to estimate volatilities and market liquidity (that is, average daily volume and open interest) to construct the portfolio that we would use from October 2009 through September 2010.

The first thing to notice about this portfolio is that the contract weights reveal fairly high correlations within sectors and almost no correlation across sectors. As a result, the volatilities for each of the contracts within a sector tend to be low relative to the sector's target volatility. In contrast, if you square each sector's volatility, add the four together, and take the square root, you obtain a number that is very close to the annualized target volatility of $300,000,000. This is almost exactly what one expects from independently distributed random variables. That is, the sum of the variances is the variance of the sum.

The second thing to notice is the number of markets capped in each sector. In equity markets, only the DJIA Mini contract was capped because of its market size, and then it was capped only a little. In interest rate markets, five markets were capped, and three of these were 3-month interest rate contracts. By design, we did not cap any of the foreign currency positions, arguing that these markets are amply liquid. And in fact, the cash market trades associated with these position sizes represent comparatively small trades. In the commodities sector, we found that five markets were capped.

Simplifying assumptions

Armed with the price data and the portfolios, we can now turn to implementing the models. Before doing any calculations, however, we need to enumerate the various simplifying assumptions and decisions we made. In particular, we used:

- Same parameters for all markets
- Same volatility look back
- Same liquidity constraints
- No stops/always in
- Same execution assumptions
- Same transaction cost per contract
- Same portfolio for a whole year with no re-sizing
- No subscriptions or redemptions
- No single currency margining costs
- 75% of the 3-month Treasury bill rate on cash (when reckoning net asset values)

Every one of these assumptions touches on some aspect of the business of trading that requires study, refinement, finesse, and flexibility. This list also provides a useful point of reference for conversations with actual traders about how they deal with these very practical problems.

Executing trades

In practice, our execution rules were these. For trades generated by signals from a model, we assumed that the trades were done at the next day's closing or settlement price. For trades required for rolls, we used the closing or settlement prices for the day determined by the roll rule. In both cases, we taxed the trades at $50 per side, which was probably about right on average for outright trades determined by signals but was almost certainly much too high for roll trades.

Each calendar year's results

Given the time line for portfolio rebalancing that we used here, each calendar year's results reflect the gains and losses on two different portfolios – one for the period running from January through September and one for the period running from October through December.

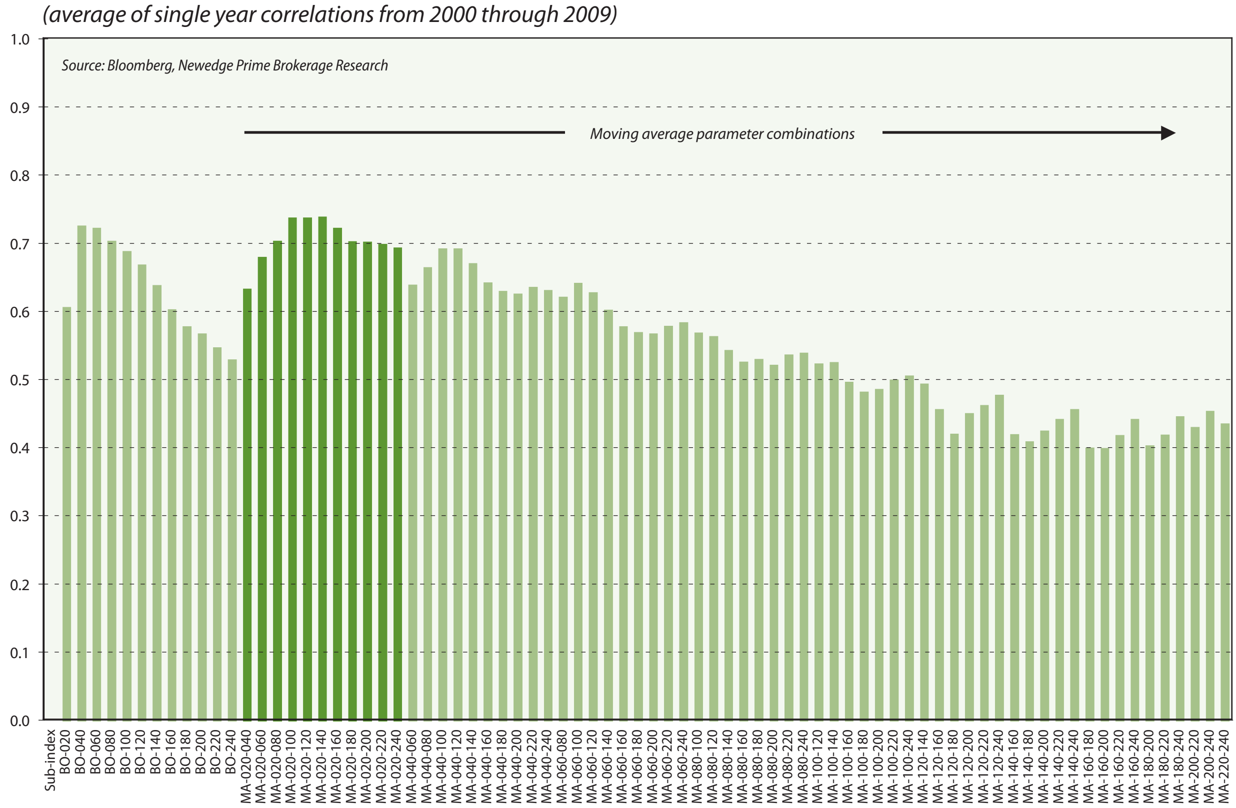
How did the models do?

We turn now to the results and review the performance of the models from three different perspectives. First, we consider the correlation of each model's weekly returns with those on the Newedge CTA Trend Sub-Index. Second, we review the volatility performance of the models and compare them with the volatility of returns on the Newedge CTA Trend Sub-Index. Third, we take a look at when and where the models made money – which years and which markets.

Correlation with the Newedge CTA Trend Sub-Index

The correlations of weekly returns shown in Exhibit 9 are the averages of 10 single year correlation estimates from 2000 through 2009. The results for the range breakout models for look back periods ranging from 20 to 240 days are shown at the left of the exhibit. The results of the moving average models are arrayed to the right and are grouped by the number of "fast" days so that all results for a fast-day moving average using 20 days are grouped together in order of increasing numbers of slow days. So the results for the 20/40 parameter choice is first on the left, followed by 20/60, 20/80, and so on to 20/240. The very last vertical bar on the right represents the results for 220/240 combination. With this way of ordering the results, one moves from faster systems on the left to slower systems on the right – both within a group with a common number of fast days, and across groups as the number of fast days increases.

Exhibit 9
Correlations with weekly returns on Newedge CTA Trend Sub-Index
(average of single year correlations from 2000 through 2009)



We found that both types of models – range breakout and moving average crossover – were capable of producing respectably high correlations. For the range breakout model, the highest average correlations were produced by look-back periods of 40 and 60 days. For the moving average systems, the highest correlations were produced by the 20/100, 20/120, and 20/140 parameter combinations. In both types of models, the correlations were generally higher for faster models and tended to decline as the models slowed down and the holding periods increased.

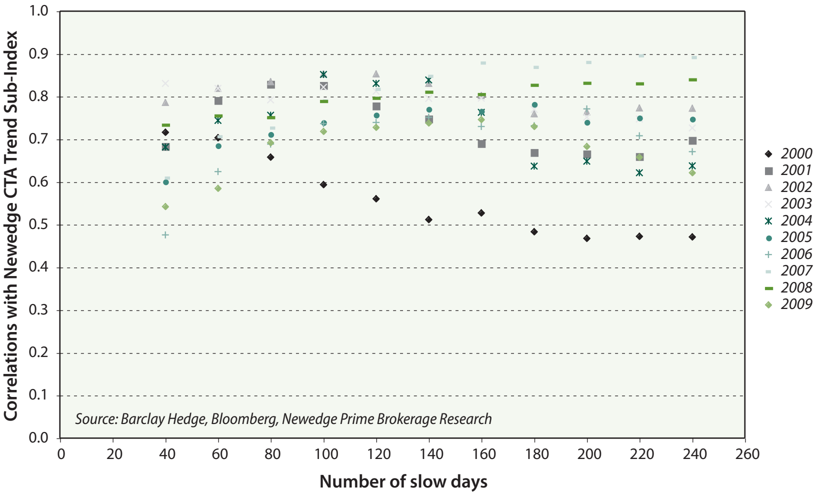
We find these results encouraging. If we are looking for a single, basic trend following model and parameter combination to represent a benchmark for an individual trend following CTA, a correlation of 0.70 or more is perfectly adequate. For one thing, it is a value that looks like the pair-wise correlations in Exhibit 3 for our 11 trend following CTAs. For another, if you fast forward to Exhibit 17, you will see that a 20/120 moving average model produces correlations that would cause it to fall into a correlation cluster with six of the 11 trend followers in 2009.

As it is, in choosing between the breakout and moving average models, we came down in favor of the moving average model partly because its average correlation performance was slightly greater than the highest breakout correlations. And within the moving average models, the eye is drawn to the 20/120 model's results because it falls between the 20/100 and 20/140 models, both of which seem to produce nearly identical results. Thus, 20/120 is in the middle of what appears to be a stable range of parameter choices.

Exhibit 10

Correlations of moving average model returns with Newedge CTA Trend Sub-Index

(Number of fast days = 20)



Our choice of the 20/120 model is reinforced somewhat by the evidence provided in Exhibit 10, which shows how the correlations behaved by year for each choice of slow days. In this exhibit, one can see that the annual correlation estimates for the 20/120 combination are very slightly more tightly clustered than for the 20/100 and 20/140 combinations. And all three are more tightly grouped than their faster and slower neighbors.

Volatility

The average return volatilities are shown in Exhibit 11, in which the left-most vertical bar represents the average return volatility for CTAs in the Newedge CTA Trend Sub-Index from 2000 through 2009. The other bars, which are organized in the same way as those in the correlation exhibit, show that the result of our experiment produced an average volatility of returns just slightly less than 20% and very close to the average return volatility that trend followers exhibited for the same period.

The similarity in the average volatilities of actual trend followers and of our trend following models is in part accidental. Consider Exhibit 12, which tracks the two sets of volatilities year by year. The line with circles represents the history of average annual return volatilities for CTAs in the Newedge CTA Trend Sub-Index. The vertical bars with the shaded bans show the range of volatilities for the 78 different model/parameter combinations. The narrow vertical line represents the range from highest to lowest volatilities, while the gray band represents one standard deviation of the distribution of realized volatilities.

From the history of return volatilities for the trend following CTAs, it seems that they had been reducing their volatility targets as the decade progressed. During the first four years, their return volatilities were all above 20%, while their average return volatility during the last six years was 15.8%. It is also apparent that trend following CTAs managed to control their return volatilities during 2008 and early 2009, years that were heavily affected by the financial crisis.

Exhibit 11

Annualized return volatilities

(Averages of single-year volatilities from 2000 through 2009)

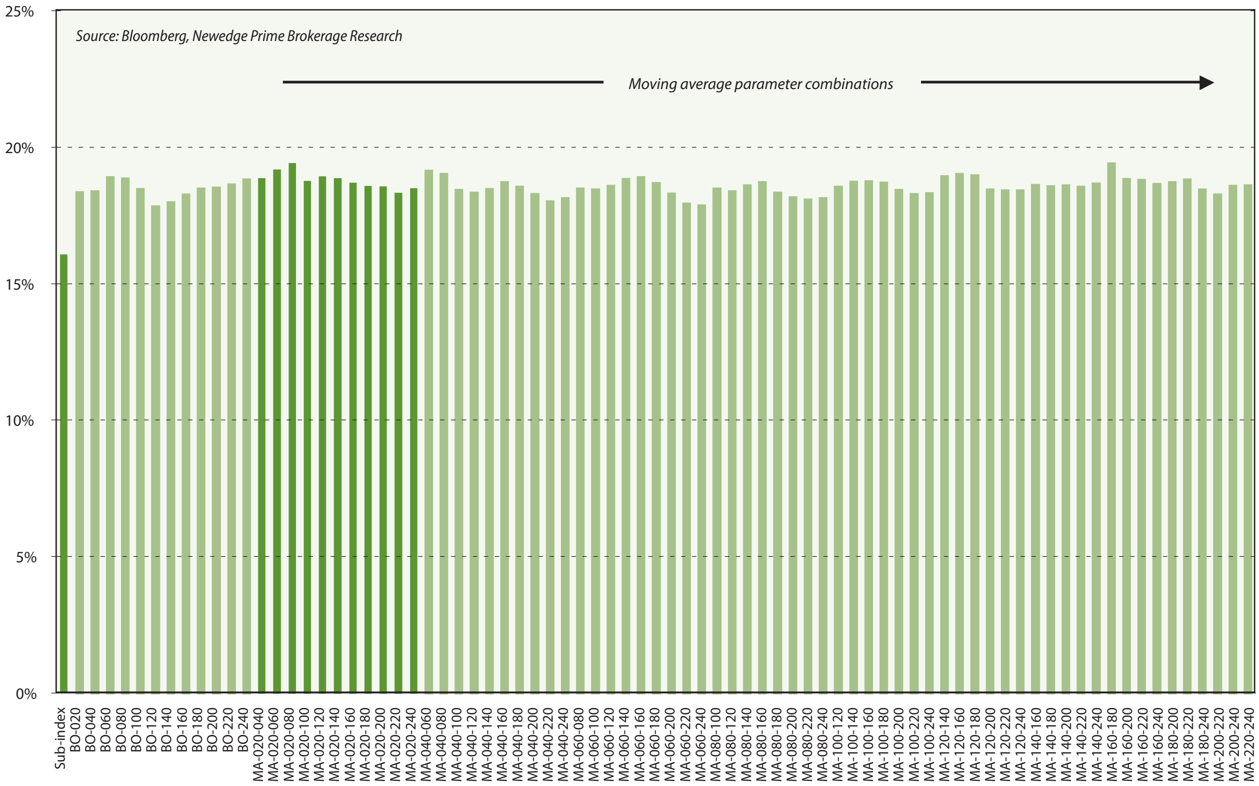
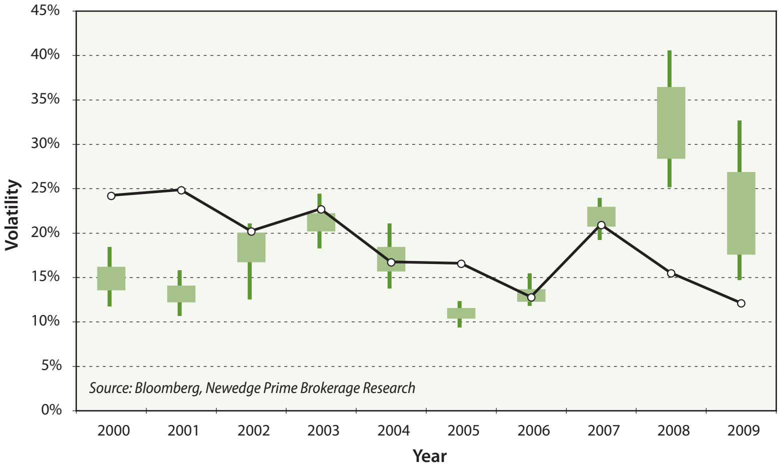


Exhibit 12

Annualized return volatilities for CTAs in the Newedge CTA Trend Sub-Index and all model/parameter combinations

(Shaded bands contain 1 standard deviation, ends of vertical lines represent minimum and maximum values)



From the history of return volatilities for the 78 model/parameter combinations, we see that for the first eight years of the experiment, the volatility forecasting approach we used was fairly effective and produced results that were not very different from what the industry produced. It is also apparent that the two-year look back and one-year look forward approach did not handle the U.S. financial crisis very well and resulted in volatilities for 2008 and 2009 that were roughly double what the industry managed to achieve.

Looking back to Exhibit 10, we find that the higher volatility did not hurt the correlations of the moving average model returns with those of the Newedge CTA Trend Sub-Index. And, since high and stable correlation is our main objective, the high volatility produced by our approach was more instructive than bothersome. On the other hand, if we find ourselves wanting to produce a benchmark that captures the volatility characteristics of the industry as well, it is clear that we would need to revisit the question of how best to forecast volatility and to adjust our portfolio weights.

Profits and losses

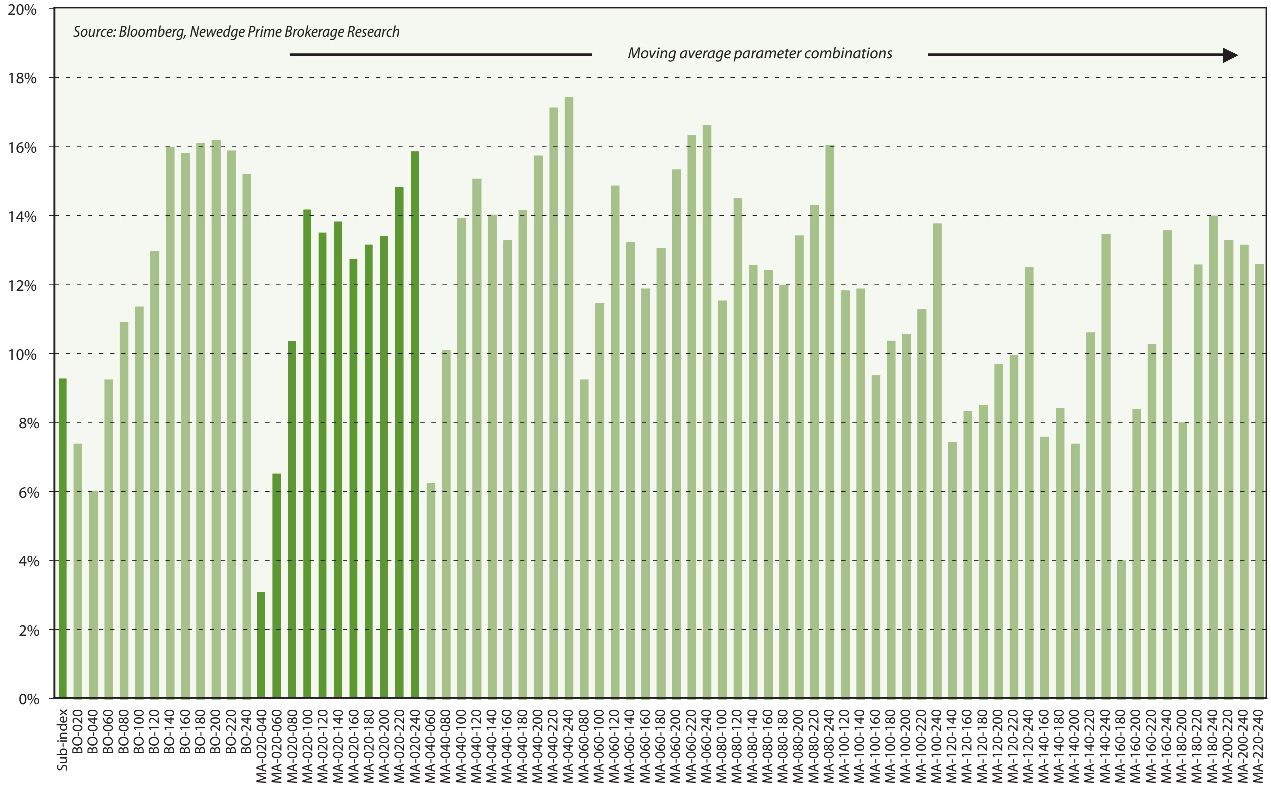
Over the ten years, the Newedge CTA Trend Sub-Index and all of the model/parameter combinations made money. In Exhibit 13, the left-most vertical bar, which represents the Newedge CTA Trend Sub-Index, shows that this subset of the industry yielded an average annualized return of 9%.

Two things stand out in this exhibit. The first is that most of the model/parameter combinations produced higher returns than did the Newedge CTA Trend Sub-Index. The second is that the faster models

Exhibit 13

Annualized returns

(Averages of single-year returns from 2000 through 2009)



tended not to do as well as the slower models. The first observation can be explained mainly by the fact that the sub-index returns were net of management and performance fees, while the model returns are gross. We deal with this difference later when we construct a hypothetical net asset value history for the 20/120 moving average model. The second observation affords us an opportunity to review the influence of trading velocity and transactions costs.

Exhibit 14 provides a summary of the transaction history of the moving average models that used 20 days to calculate the fast moving average in 2009. As the number of slow days increases from 40 to 240, you can see that the number of outright contracts traded falls from 1,396,692 to 200,976. You can also see that the number of contracts rolled is exactly the same for all of the parameter choices, again because the models were always in the market and the position sizes were all the same.

From the cost calculations that we have provided, it is quite clear that trading velocity can have a substantial effect on net returns. With our $50 per side assumption, the $60 million difference in outright trade costs would have amounted to a difference of 3% in net returns on a $2 billion portfolio. As a result, trading costs explain quite a bit, but by no means all, of the lower returns produced by the higher velocity parameter choices.

Exhibit 14

Transaction costs example

(2009, moving average models with fast days = 20)

Number of slow days	# of outright contracts traded	# of contracts rolled	% contracts rolled	Outright cost (at $50)	Roll cost (at $50)	Roll cost (at $10)	Total cost (at $50)	Total cost (at $10)
40	1,396,692	535,557	28%	$69,834,600	$53,555,700	$10,711,140	$123,390,300	$80,545,740
60	865,718	535,557	38%	$43,285,900	$53,555,700	$10,711,140	$96,841,600	$53,997,040
80	581,574	535,557	48%	$29,078,700	$53,555,700	$10,711,140	$82,634,400	$39,789,840
100	466,700	535,557	53%	$23,335,000	$53,555,700	$10,711,140	$76,890,700	$34,046,140
120	392,792	535,557	58%	$19,639,600	$53,555,700	$10,711,140	$73,195,300	$30,350,740
140	338,792	535,557	61%	$16,939,600	$53,555,700	$10,711,140	$70,495,300	$27,650,740
160	303,968	535,557	64%	$15,198,400	$53,555,700	$10,711,140	$68,754,100	$25,909,540
180	288,078	535,557	65%	$14,403,900	$53,555,700	$10,711,140	$67,959,600	$25,115,040
200	298,016	535,557	64%	$14,900,800	$53,555,700	$10,711,140	$68,456,500	$25,611,940
220	196,628	535,557	73%	$9,831,400	$53,555,700	$10,711,140	$63,387,100	$20,542,540
240	200,976	535,557	73%	$10,048,800	$53,555,700	$10,711,140	$63,604,500	$20,759,940

Source: Newedge Prime Brokerage Research

Exhibit 15

Round turns per $1 million
(indexed)

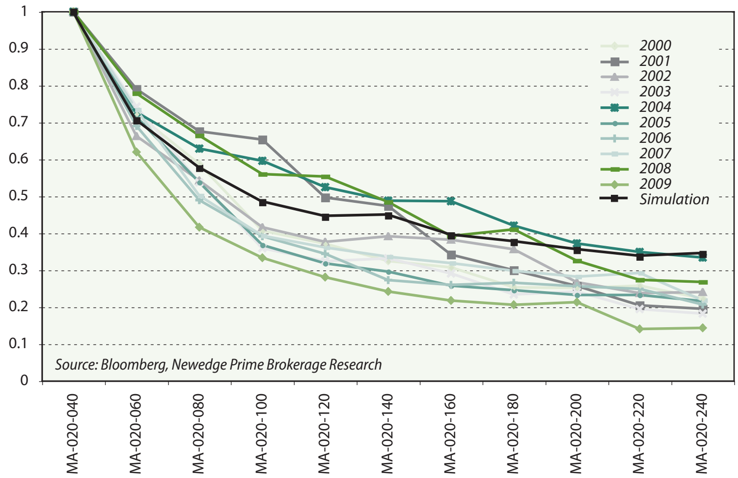


Exhibit 16

Net dollar gains and losses for the 20/120 moving average model (Newedge Trend Indicator)
($2 billion portfolio with realized volatilities shown in Exhibit 12)

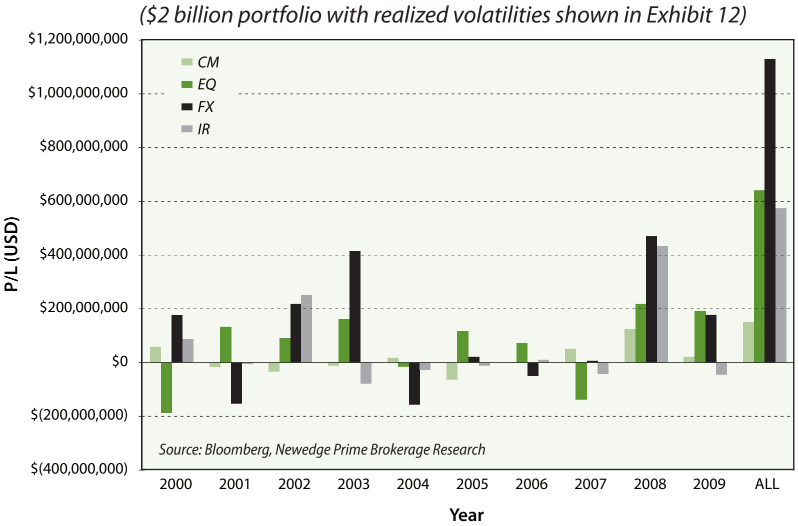
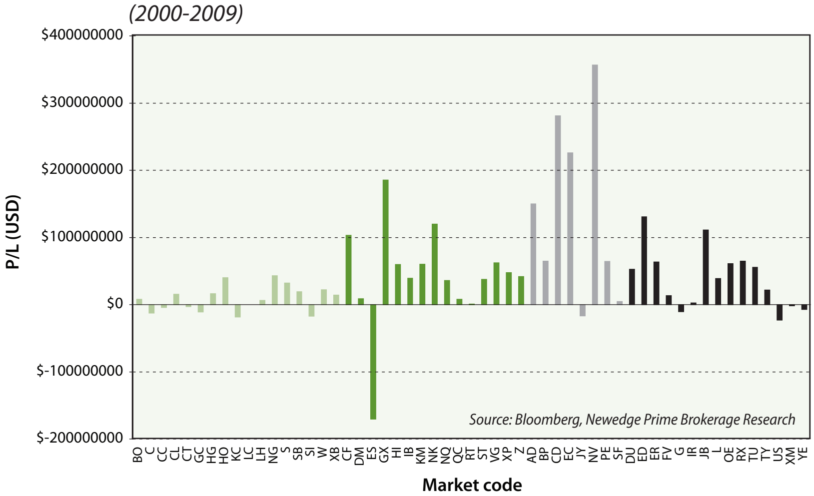


Exhibit 17

Total dollar gains and losses for the 20/120 moving average model (Newedge Trend Indicator)
(2000-2009)



It is also clear that the costs of rolling contracts can loom large. The difference between $50 per side and $10 per side when rolling more than half a million contracts a year is worth about 2% in net return.

Exhibit 15 is meant to provide a reasonableness check on our simulated trade experience with the moving average models. The metric here is round turns per million, which is a standard measure for comparing trading velocities among CTAs. The solid line that corresponds to "Simulation" shows how a moving average model with the fast average based on 20 days would have traded a market in which the mean drift or change is zero and the volatility is constant. What we find is that our trend following models when applied to actual price data produced similar results, but in most cases tended to trade slightly fewer contracts. By itself, this is interesting because it is a result that one would expect in a world in which prices exhibit more trends – or positive serial correlation in changes – than one finds with a perfectly efficient random price process.

The higher returns can also be explained in part by the fact that our approach to targeting return volatility produced a return volatility for 2008 that was more than double the target value. And, as shown in Exhibit 16, 2008 was probably the strongest year of the ten for the 20/120 moving average model, which made money in all four sectors. As a result, our models all produced gains in 2008 that were more than double what they would have been with tighter risk controls.

Another important difference between our approach and what one would find in the practices of actual trend followers is illustrated in Exhibit 17, which shows the average gain or loss by market. Here we find that the 20/120 model made money in nearly every market over the entire 10-year period with the notable exception of E-mini S&Ps, which is one of the most liquid and actively traded equity markets in the world. In a broadly diversified, volatility weighted portfolio, these losses would not put much drag on the overall portolio's performance. But such a pronounced source of losses would certainly be an object of intense scrutiny by any real trading firm.

Exhibit 18

Correlation cluster results of daily returns for CTAs in the 2009 Newedge CTA Index

Designation	CTA	Correlation																				
		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
	1 Crabel Capital (Multi-Product)	1.00	0.67	0.51	-0.16	0.08	0.00	-0.01	-0.01	-0.13	-0.09	0.19	0.25	0.22	0.26	0.24	0.22	0.18	0.36	0.09	0.09	0.30
	2 R.G. Niederhoffer (Diversified)	0.67	1.00	0.48	-0.06	0.10	0.06	0.01	0.00	-0.01	-0.19	0.16	0.23	0.25	0.07	0.18	0.15	0.16	0.34	0.18	0.22	0.23
	3 QIM (Global)	0.51	0.48	1.00	0.34	0.44	0.33	0.42	0.42	0.34	0.27	0.46	0.34	0.44	0.37	0.40	0.41	0.24	0.19	0.12	0.13	0.32
TF	4 Newedge Trend Indicator	-0.16	-0.06	0.34	1.00	0.70	0.69	0.79	0.79	0.73	0.65	0.58	0.27	0.43	0.40	0.45	0.44	0.10	0.09	0.26	0.15	0.14
TF	5 Altis Partners (GFP Composite)	0.08	0.10	0.44	0.70	1.00	0.72	0.78	0.78	0.70	0.54	0.74	0.66	0.73	0.63	0.71	0.60	0.27	0.17	0.19	0.24	0.21
TF	6 Campbell & Co., Inc. (FME Large)	0.00	0.06	0.33	0.69	0.72	1.00	0.82	0.82	0.67	0.67	0.71	0.51	0.62	0.50	0.75	0.63	0.30	0.36	0.25	0.07	0.21
TF	7 Graham Capital (Diversified)	-0.01	0.01	0.42	0.79	0.78	0.82	1.00	1.00	0.69	0.79	0.75	0.43	0.55	0.50	0.59	0.48	0.20	0.20	0.10	0.13	0.14
TF	8 Graham Capital (K4)	-0.01	0.00	0.42	0.79	0.78	0.82	1.00	1.00	0.69	0.79	0.74	0.43	0.55	0.49	0.58	0.48	0.20	0.20	0.09	0.12	0.13
	9 IKOS Partners (Financial USD)	-0.13	-0.01	0.34	0.73	0.70	0.67	0.69	0.69	1.00	0.55	0.55	0.37	0.58	0.35	0.55	0.53	0.24	0.14	0.14	0.20	0.30
TF	10 Sunrise Capital (Diversified)	-0.09	-0.19	0.27	0.65	0.54	0.67	0.79	0.79	0.55	1.00	0.69	0.15	0.37	0.50	0.45	0.37	0.20	0.13	0.06	-0.16	0.15
TF	11 Transtrend, B.V. (Admiralty Fund)	0.19	0.16	0.46	0.58	0.74	0.71	0.75	0.74	0.55	0.69	1.00	0.53	0.64	0.54	0.66	0.60	0.17	0.32	0.16	0.20	0.23
TF	12 Aspect Capital (Diversified)	0.25	0.23	0.34	0.27	0.66	0.51	0.43	0.43	0.37	0.15	0.53	1.00	0.79	0.62	0.79	0.77	0.37	0.35	0.21	0.52	0.27
TF	13 Brummer & Partners (Lynx)	0.22	0.25	0.44	0.43	0.73	0.62	0.55	0.55	0.58	0.37	0.64	0.79	1.00	0.66	0.78	0.77	0.30	0.39	0.27	0.31	0.50
TF	14 Chesapeake Capital (Diversified)	0.26	0.07	0.37	0.40	0.63	0.50	0.50	0.49	0.35	0.50	0.54	0.62	0.66	1.00	0.72	0.71	0.37	0.27	0.27	-0.03	0.32
TF	15 Millburn Ridgefield (Diversified)	0.24	0.18	0.40	0.45	0.71	0.75	0.59	0.58	0.55	0.45	0.66	0.79	0.78	0.72	1.00	0.86	0.46	0.41	0.25	0.17	0.36
TF	16 Winton Capital (Diversified)	0.22	0.15	0.41	0.44	0.60	0.63	0.48	0.48	0.53	0.37	0.60	0.77	0.77	0.71	0.86	1.00	0.53	0.42	0.30	0.25	0.31
	17 Grossman Asset Mgmt. (Currency)	0.18	0.16	0.24	0.10	0.27	0.30	0.20	0.20	0.24	0.20	0.17	0.37	0.30	0.37	0.46	0.53	1.00	0.19	0.18	0.09	-0.09
	18 FX Concepts (Global Currency)	0.36	0.34	0.19	0.09	0.17	0.36	0.20	0.20	0.14	0.13	0.32	0.35	0.39	0.27	0.41	0.42	0.19	1.00	0.44	0.16	0.32
	19 FX Concepts (Dev. Market Curr.)	0.09	0.18	0.12	0.26	0.19	0.25	0.10	0.09	0.14	0.06	0.16	0.21	0.27	0.27	0.25	0.30	0.18	0.44	1.00	0.04	0.22
	20 Eagle Trading Systems (Yield)	0.09	0.22	0.13	0.15	0.24	0.07	0.13	0.12	0.20	-0.16	0.20	0.52	0.31	-0.03	0.17	0.25	0.09	0.16	0.04	1.00	-0.03
	21 Boronia Capital (Diversified)	0.30	0.23	0.32	0.14	0.21	0.21	0.14	0.13	0.30	0.15	0.23	0.27	0.50	0.32	0.36	0.31	-0.09	0.32	0.22	-0.03	1.00

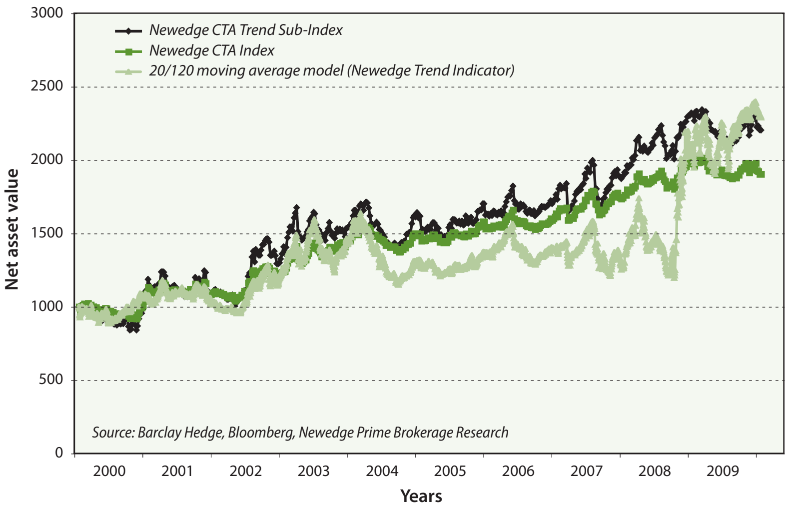
Source: Barclay Hedge, Bloomberg, Newedge Prime Brokerage Research

The Newedge Trend Indicator

We have chosen to use a 20/120 moving average model as the Newedge Trend Indicator because of its solid correlative properties. In Exhibit 1, we showed that a 20/120 moving average model produced returns that exhibited a 0.67 correlation with the returns on the Newedge Trend Sub-index. As it was, we chose that particular parameter and model combination partly because it had produced – as shown in Exhibits 9 and 10 – the highest and tightest correlation fits for the ten years covered by this study.

Exhibit 19

Net asset values for Newedge CTA Index, Newedge CTA Trend Sub-Index and 20/120 moving average model (Newedge Trend Indicator)



Our choice was reinforced by the correlation cluster analysis provided in Exhibit 18, which shows that the 20/120 moving average model fell into a cluster that contained Altis, Campbell, Graham, Sunrise, and Transtrend. In other words, it would have been nearly indistinguishable from CTAs who are widely recognized as trend followers.

For the sake of completeness, we have produced a hypothetical net asset value history for the Newedge Trend Indicator as if it were initiated on the first business day of January 2000. For the purposes of producing this hypothetical series, we assumed a 2 and 20 fee structure. As shown in Exhibit 19, the trend indicator did a good job of tracking the Newedge CTA Index and Trend Sub-index, albeit with lower returns, through most of the decade.

Next steps

Although we found in this round of research that the 20/120 moving average model exhibited the greatest consistency in its correlation with returns on the Trend Sub-index, we also recognize opportunities for improving both the correlation and volatility of returns exhibited by the Trend Indicator. For example, had we been able to reduce the volatility of returns in 2008 and 2009, the resulting hypothetical net asset value history would have conformed much more closely to those of actual CTAs. And because volatility plays a fairly important role in the estimation of correlations, tighter risk controls might easily improve the model's return correlations with trend followers' returns.

Early comments on this research have also suggested other areas to explore when working to improve return correlations. These include:

- Sector weights
- Choice of parameters
- Blending of two or more models and/or parameter sets

For example, we have heard that a number of trend followers employed a higher weight for commodities than we did and a lower weight for equities. Also, we know that the 20/120 moving average model did not exhibit the highest return correlation in all of the ten years. Early in the decade, faster moving average models produced higher correlations, while later in the decade, slower models did better on this measure. For us, the challenge will be to see if we can find a way to anticipate correlations better and to adapt to them in a way that makes sense. We know, too, that actual CTAs use a blend of models, and perhaps we can improve correlations by blending two or more models.

Our guiding principles in this ongoing work to improve the Trend Indicator's performance will be sense and simplicity. We will depart from the basic assumptions used in this round of research only with the greatest reluctance. Instead, we will focus on innovations that promise substantial improvements in correlation without violating the spirit of this benchmark.