Hedging the S&P 500 Index:
ZIG when the Market Zags

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Abstract

This paper describes development of a trading strategy (ZIG) that is shown to be an effective hedge against holding the S&P 500 index and has good absolute performance in its own right.

The case has been made that a Buy & Hold (B&H) of a low fee S&P 500 Index fund, such as Vanguard's 500 Index Fund (VFINX), is the best option for most investors.[1] In recent decades, the stock market has undergone a massive repricing about once per decade, with smaller setbacks along the way. Many investors, especially those who are retired or approaching retirement age, simply can't tolerate drawdowns of 50% or more, and often exit their long positions near market lows.

Active investment managers continue to seek ways of mitigating the risk, or even take advantage, of market drawdowns by using inverse equity investment

products; however, it is well known that bear market rallies can be very violent. The expression "rip your face off short-covering rally" is often used to describe these events. An extreme case in point: On January 3, 2001 the Fed surprised the market with an interest rate cut, and the NDX rallied by nearly 20% in a single day, catching many active managers 2X short for a nearly 40% one day loss. ZIG provides a way to hedge a B&H position of a portfolio with potentially much less risk than a direct short of the major indexes. There is also a case to be made that hedging with the ZIG strategy may provide the additional advantage of long term (LT) capital gains in the B&H portion of the portfolio.

The performance metrics in Table 1[2] include approximately 30 years of combined back testing, out–of-sample, and real-time performance. Real-time only performance for 2018 is shown in Table 2. The strategy has remained unchanged since 12/29/2017 when the strategy was frozen. Performance metrics are for ZIG alone, in combination with Vanguard's 500 Index Fund (VFINX), and a 75% portfolio ZIG position in combination with a 25% position in a hypothetical leveraged 2xS&P 500 Index fund (without dividends). Maximum Drawdowns values are calculated based on both a daily and monthly basis. Tables 1 & 2 assume daily rebalancing between ZIG and the other funds. The report will compare the effect of monthly and quarterly rebalancing.

Symbol	Strategy	Annualized, %	Daily MDD, %	Monthly MDD, %	Correlation, %[3]	Beta[4]
VFINX	Buy & Hold	9.29	-55.26	-51.0	100.00	1
ZIG	ZIG only	11.69	-21.79	-18.9	-17.45	-0.13
ZIG/VFINX	50%/50%	11.27	-21.83	-14.0	75.52	0.43
ZIG/2xS&P	75%/25%	13.03	-23.54	-17.4	57.88	0.40

Table 1 - ZIG Performance (testing & real-time: 7/20/1989 – 12/31/2018)

Symbol	Strategy	Annualized, %	Daily MDD, %	Monthly MDD, %	Correlation, %	Beta
VFINX	Buy & Hold	-4.54	-19.40	-13.6	100.00	1
ZIG	ZIG only	13.91	-6.93	-4.5	-14.59	-0.09
ZIG/VFINX	50%/50%	4.89	-7.23	-3.3	81.86	0.45
ZIG/2xS&P	75%/25%	7.21	-6.39	-3.7	66.93	0.43

Table 2 - ZIG Real-time Only Performance (2018)

ZIG can certainly be combined with other active management strategies to provide an even more neutral investment strategy.

The trading strategy uses funds that have a low, and in some cases negative, correlation with the S&P 500 Index; specifically, the Rydex Strong and Weak Dollar funds (RYSDX/RYWDX), along with the Rydex Long and Short government bond funds (RYGBX/RYJUX). The strategy was developed using FastBreak Pro[5] and tested on thirty years of data from Investors FastTrack (FastTrack). The optimization period was between 1993 and 2017 with out-of-sample results from 1989 to 1992 used in the optimization process.

Chart 1[6] displays the equity curve for ZIG only (red), VFINX (green), a 50%/50% weighting between ZIG and the VFINX (yellow), a 75%/25% weighting between ZIG and a 2x leveraged S&P 500 Index fund (blue):

Chart 1 - Equity Curves (Log) for ZIG and Combinations of ZIG with Other Funds

The Rydex funds have existed for a number of years; however, this analysis extends the historical data with synthetic data. The process used to create the synthetic data is described in this paper.

Seeking a Hedge

Investment professionals are constantly searching for ways to hedge equity positions. There are investments that tend to have low or negative correlation with the S&P 500 Index. Some of the most common are: US Government bonds, gold and gold mining funds, energy funds, and currency funds. We restricted our universe to the Rydex funds for a few reasons:

- Trader friendly
- Available in the Jefferson National (now Nationwide) annuity product.
- Funds in all the traditional areas just mentioned, except for a fund that holds physical gold, but they do have a gold mining fund.
- One of the few companies that have strong/weak dollar funds. Note: ProFunds also meets these criteria except the ProFunds currency funds are only 1x beta, and the Rydex currency funds are 2X beta and provide better results.

Note: There are several classes of the Rydex funds. The class with the longest history was used for this study. If using other classes the results will be slightly different.

Table 3 shows a few statistics on the above mentioned Rydex funds (over the life of each fund) compared to VFINX:

Symbol	Fund Name	Annual, %	MDD, %	Correlation w/VFINX, %	Beta w/VFINX	Inception
RYGBX	Gov Long Bond	5.53	-36.05	-41.02	-0.4	1/3/1994
RYSDX	Strengthening Dollar 2x	-0.61	-43.69	-23.23	-0.2	5/25/2005
RYWDX	Weakening Dollar 2x	-2.95	-56.49	23.22	0.2	5/26/2005
RYPMX	Precious Metals	-0.41	-81.27	37.27	0.82	12/2/1993
RYJUX	Inverse Gov Bond	-6.30	-70.26	41.04	0.34	3/3/1995
RYEIX	Energy	0.41	-63.97	78.23	1.3	4/24/1998

Table 3 – Rydex Funds Considered for the Strategy

Clearly, the Government bond and dollar funds are desirable for diversification because of their negative or low correlation. The energy fund is highly correlated with the S&P 500 and tends to be volatile, so it was excluded from this study. Although the precious metals fund has a low correlation, these funds are notoriously difficult to trade. Finally, the inverse government bond fund has modest correlation, but we will keep it as we enter what may be an increasing interest rate environment.

Creating Synthetic Data

The inception date for all the funds of interest is shown in Table 3. Although there is a significant amount of historical data, the currency funds are a weak link. It is desirable to extend the historical data back to at least the turbulent late 1990s and the tech bubble crash of 2000. One advantage of the Rydex funds is

that they are indexed to the Dollar Index (DXY-Z in the FastTrack database) and the DXY-Z is available in the database beginning on 9/1/1988:

Symbol	Name	Correlation w/DXY-Z, %	Beta w/DXY-Z
RYSDX	Strengthening Dollar 2x	95.30	1.99
RYWDX	Weakening Dollar 2x	-95.30	-2.00

Table 4 – Rydex Funds Compared to the Dollar Index (DXY-Z)

The high correlation between the Rydex funds and the Dollar Index allows creation of synthetic data for the currency funds from 9/1/1988 until 2005 when the actual fund data become available. The process for creating the data is simply to create a data series that changes by 2X the daily change of DXY-Z. Once the actual funds become available in 2005, the daily changes in the fund data are used to append additional history to the synthetic data. Of course the synthetic price data isn't the same as the actual fund price data, but for this study, we only care about the rate of change (ROC) of the price data.

If we can extend the currency fund data back to 1988, can we do the same with the Government bond fund and Inverse bond fund? The answer is yes. The key is finding a highly correlated surrogate fund or index that has a long price history. FastTrack has the ability to search its entire database to find highly correlated funds or indexes. Searching the database it was found that the

Vanguard Long Term Treasury Bond fund (VUSTX) has a very high correlation with both RYGBX and RYJUX:

Symbol	Name	Correlation w/VUSTX, %	Beta w/VUSTX
RYGBX	Gov Long Bond	97.39	1.5
RYJUX	Inverse Gov Long Bond	-96.31	-1.24

Table 5 – Rydex Bond Funds Compared to VUSTX

The correlation and beta are of course negative in the case of the inverse bond fund. The same technique used to create the synthetic data for the currency funds was used to create synthetic data for the bond funds as well. *Note: The technique used to create the synthetic data also adjusts for average daily over- or under-performance between the surrogate and the actual funds. This is a very minor adjustment for the currency funds (< 1.5%/year) but a more significant for the bond funds (~3 to 4%/year). The exact process for adjusting the synthetic data is beyond the scope of this paper.*

With the data extending back to 1988, here is a graphical representation of the synthetic trading funds compare to VFINX (blue): Government Bond (red), Inverse bond (green), Strong Dollar (yellow) and Weak Dollar (purple):

Chart 2 - Synthetic Rydex Fund Data used in the Strategy

In the chart above, clearly there is a lot of activity not correlated with the VFINX (blue).

Table 6 contains a summary of statistics for the synthetic data. The Correlation and Beta are with respect to VFINX. *Note: the synthetic data symbols ends in "1" to distinguish them from the actual fund symbols which end with an "X":*

Symbol	Name	Correlation %	Beta	Inception
RYGB1	VUSTX+RYGBX Rydex Gov Long Bond	-21.22	-0.19	9/1/1988
RYJU1	VUSTX+RYJUX Rydex Inverse Gov Bond	22.01	0.17	9/1/1988
RYSD1	DXY-Z+RYSDX Rydex Strengthening Dollar	-5.12	-0.05	9/1/1988
RYWD1	DXY-Z+RYWDX Rydex Weakening Dollar	5.12	0.05	9/1/1988

Table 6 - Comparing the Synthetic Fund Data to VFINX

We note that the correlations for our synthetic/actual data series are somewhat different than the "actual only" data. This isn't entirely unexpected because we are now comparing more than twice as much historical data.

Strategy Optimization Process

FastBreak Pro (FBPro) was used to build the trading strategy. FBPro can be used to build momentum/trend following strategies using a Genetic Algorithm (GA) optimizer to select both the strategy options, i.e., stops, buy filters etc., as well as the parameter values for the options. *Note: In the optimization process VMMXX was used for the money market fund because it was available for the entire testing period. This is one of the best performing money market funds available, so the use of other money market funds will likely decrease performance slightly.*

Avoiding Over-Optimization

Perhaps the most serious concern with trading system development is the problem of over-optimization[7] or overzealous data mining, and this issue must be addressed. Our intent in extending the historical testing data was just a part of addressing this issue. Use of more data, with a greater number of trades under numerous market conditions, can help avoid over-optimization.

As is very common in strategy development[8], FBPro divides the available historical data into In-sample (IS) and Out-of-sample (OS) time periods. The IS

data is used in parameter selection and the OS data is used to determine when over-optimization is beginning to take place. How this works will become clear as we describe the process.

GA optimization has what we will call an "intrinsic natural ability" to avoid over-optimization. By nature, GA optimization tends to progress from under-optimization to over-optimization. In contrast, exhaustive search optimizations don't "evolve" to a best solution. For example, if you exhaustively test all moving average values from 10 to 100, there is no reason to think that you are progressing to over-optimization. In the testing process, a value of 89 is just as likely to be good or bad as a value of 7. This generally isn't true for GA optimization. GA optimization starts with random parameters and progressively finds solutions that are better, but at the same time, the GA optimizer will over-optimize if allowed to run excessively. This may be obvious to some, but the proof is in looking at OS results during the optimization process. The IS data is used to optimize the strategy, and the OS data is used to monitor the progression of the optimization for indications that over-optimization is beginning to take place. Most of the time, you will observe a positive progression in the OS performance as the optimized IS results steadily improve; however, a point is reached where the OS results begin to "roll over" and performance decreases,

and this is an indication that the systems are becoming over-optimized and are no longer robust. We will provide an example below.

Another indication that a system may be robust is if small changes in trading parameters do not seriously affect historical performance.[9] For example, if a moving average stop of 50 days works well and using 45 or 55 days also works nearly as well, then this could be considered a robust parameter. FBPro performs an automated sensitivity analysis of parameters. After FBPro has evaluated a trading system during optimization, two additional evaluations of the same system are made, but with a small variation in all the parameters. First, all the parameters are increased by a user-defined percentage (10% in the case of this study). Then a second evaluation of the strategy is made with these new parameters. Finally, the parameters are decreased by the same percentage and a third evaluation of the strategy is made. The performance results from the two sensitivity runs are compared to the original strategy results, and if there is a significant impact to performance, this strategy is not considered robust and the strategy is "penalized" in consideration for genetically evolving future strategies.

Another way to prevent over-optimization is to avoid using too many trading system options, often called "degrees-of-freedom"[10]. Strategies with more

options, such as excessive use of multiple stops, can lead to poor strategy performance in real time. FBPro applies a penalty for each option used by a strategy. The severity of the penalty is controlled by the user. By application of this penalty, strategies are again discounted in evolving strategies.

Choosing Options and Parameters

FBPro allows the user to either place the OS date range before or after the IS date range. Good arguments can be made for either choice. Placing the OS data after the IS optimization will give a better indication or strategy performance on recent market data. On the other hand, placing the OS testing prior to the IS date range allows more recent data to be used in the optimization process. For this study we chose to use as much recent data as possible and therefore used older data for the OS testing. The IS date range was 1/4/1993 to 12/29/2017 and the out-of-sample (OS) date range was set before the IS date range from 7/20/1989 to 12/31/1992. *Note: since we have trading data going back to 9/1/1988 you may ask why we use 7/20/1989 as the earliest date? The reason is that some data is required for initial ranking periods, stops, and buy filters.*

FBPro has a variety of ways to measure momentum or relative strength. The simplest, and the one used in this study, was to simply “rank” the funds. This

simply means that the algorithm calculates the gains for each fund in the trading strategy over a look-back period, and selects the one with the greatest percentage increase as the fund to purchase. FBPro allows the money market to either be part of the ranking process or excluded from ranking. A fund can be sold for two different reasons: another fund begins to outperform, or a stop option is triggered. At this point, the fund is sold, and a new fund is purchased. The fund to be purchased may be required to pass a "Buy Filter" option, such as being above a moving average. If none of the funds meet the purchase criteria, then the strategy defaults to the money market fund.

FBPro allows the user to select a performance parameter to maximize, typically Annual Return, and it allows the user to set goals for other parameters such as Maximum Draw Down (MDD), or trades per year. For this study, the GA optimizer was instructed to maximize annual return, and no other goals or constraints were used.

There is an option in FBPro to evolve a trading system that is combined with up to two other existing strategies or indexes. In this study, a buy & hold of the S&P500 Index was considered the other option. The assumption was that the investor held 50% of their account in the S&P 500 Index and the other 50% is traded in the trading strategy to be built. FBPro assumes daily rebalancing during

optimization, but the effect of using monthly or quarterly rebalancing has little effect, as will be shown later in this report.

Genetic Algorithm (GA) Optimization Overview

A full explanation of GAs is beyond the scope of this paper, but we include a basic explanation and the GA options that can be chosen.

Just as in natural evolution, GA optimization "evolves" the strategies by generations. In this study, the first "generation", which is built using completely random options and parameters, was set to a "population" of 100 strategies. Subsequent generations were set to 50 members in the population, and the total number of generations set to 30.

The "survival" percentage for each generation was set to 50%, which means half the previous generation is "killed off" and the remaining strategies are allowed to "mate". Just as in biological evaluation, there is a small amount of "mutation" allowed.

Optimization Results by Generation

As FBPro runs, it provides the user with a summary of the performance for the Top 10 strategies for each generation. Below is a screen shot of the FBPro optimization summary results:

GEN	AVG IS ANN	AVG OS ANN	AVG UPI	AVG MDD	AVG S/Y	AVG BETA	AVG CORR	AVG ALPHA	ANN SD	MAX ANN	MIN ANN
01	8.01	7.72	0.68	10.20	16.6	0.73	0.95	3.9	2.83	11.19(3)	3.04(1)
02	8.18	8.06	0.75	10.33	16.5	0.75	0.95	4.2	2.41	11.19(6)	3.04(2)
03	8.40	7.16	0.48	10.76	15.9	0.73	0.94	3.3	1.81	9.22(5)	3.04(4)
04	8.98	9.61	1.22	9.26	15.8	0.75	0.93	5.7	2.24	12.06(6)	6.45(4)
05	9.09	8.72	0.97	9.50	16.7	0.74	0.93	4.8	1.61	11.50(1)	6.87(3)
06	9.10	8.14	0.79	9.37	16.9	0.72	0.93	4.2	1.78	11.50(1)	6.23(5)
07	9.23	7.44	0.57	9.35	17.2	0.70	0.94	3.5	1.54	11.50(4)	5.85(7)
08	9.39	7.74	0.76	9.15	16.8	0.70	0.95	3.9	2.19	11.70(8)	4.95(2)
09	9.48	7.15	0.52	9.31	17.2	0.70	0.94	3.3	1.66	11.00(1)	4.95(4)
10	9.56	7.22	0.53	9.10	17.1	0.70	0.94	3.3	1.66	11.00(1)	5.05(7)
11	9.61	7.66	0.67	8.83	17.2	0.70	0.94	3.8	1.45	11.00(1)	5.65(8)
12	9.69	8.26	0.89	8.81	17.1	0.70	0.95	4.4	1.54	11.00(1)	6.56(6)
13	9.75	8.94	1.17	8.57	17.0	0.70	0.95	5.1	2.10	13.22(10)	6.56(9)
14	9.72	8.57	0.96	8.79	16.9	0.70	0.95	4.7	1.33	11.00(3)	7.39(5)
15	9.74	8.18	0.79	8.92	17.0	0.70	0.95	4.3	1.09	11.00(8)	7.35(2)
16	9.74	8.08	0.72	9.15	17.0	0.70	0.94	4.2	0.43	8.72(6)	7.35(4)
17	9.78	7.82	0.64	9.20	17.2	0.70	0.95	4.0	0.73	8.72(7)	6.03(5)
18	9.80	7.24	0.47	9.42	18.0	0.70	0.95	3.4	1.28	8.47(5)	4.80(1)
19	9.86	7.25	0.55	9.39	19.3	0.70	0.95	3.4	2.21	12.31(2)	4.80(3)
20	9.86	6.69	0.42	9.45	19.3	0.70	0.95	2.9	2.28	12.31(3)	4.80(4)
21	9.91	6.20	0.31	9.53	19.0	0.70	0.95	2.5	2.17	12.31(5)	4.80(7)
22	9.95	6.07	0.28	9.69	19.0	0.70	0.95	2.3	2.22	12.31(8)	4.80(7)
23	9.96	5.51	0.02	9.89	19.4	0.70	0.95	1.8	0.40	5.94(2)	4.56(10)
24	9.96	5.51	0.02	9.89	19.4	0.70	0.95	1.8	0.40	5.94(2)	4.56(10)
25	10.03	5.62	0.04	9.85	19.8	0.70	0.94	1.9	0.25	5.94(5)	5.29(6)
26	10.03	5.47	0.02	9.83	19.9	0.70	0.94	1.7	0.36	5.94(7)	4.71(3)
27	10.07	5.54	0.04	9.95	20.0	0.70	0.94	1.8	0.36	5.91(1)	4.71(6)
28	10.07	5.54	0.03	9.96	20.2	0.70	0.94	1.8	0.35	5.91(1)	4.71(7)
29	10.07	5.52	0.03	9.99	20.2	0.70	0.94	1.8	0.38	5.91(1)	4.71(9)
30	10.14	5.61	0.04	10.06	20.1	0.70	0.94	1.9	0.31	5.91(2)	5.05(1)

Table 7 - FastBreak Pro Optimization Results by Generation

"Gen" is simply the generation, "Avg IS Ann" is the average annual return for the top 10 trading systems in the IS data range for a given generation, "Avg OS Ann" is average annual return for the top 10 trading systems in the OS data range. The remainder of the performance parameters are the averages for the top 10 strategies in the out-of-sample time period: UPI – Ulcer Performance Index, MDD, switches/year, beta, correlation to a user defined index – in this study the S&P 500 Index, Alpha, Standard Deviation (SD) of the OS annual returns

for the top 10 strategies, and finally the maximum and minimum annualized return for the top 10 strategies. For example, in generation 13, the best strategy had an OS annualized return of 13.22% and the worst for that generation was 6.56%. *Note: The results in the table assume a 50/50 blend of the evolving strategies with the S&P 500 Index.*

As you can observe, the IS annualized performance increases with each generation – as expected. The only time you may see the IS performance decline is if the user placed other goals, such as a maximum number of switches per year (trades), for the optimization process to consider. Next, notice that the OS annual return generally increases until it is apparent that strategies are beginning to become over-optimized. Clearly, with generation 14, the OS performance is beginning to roll off. We see this not only in the OS annual return, but also in UPI and the best maximum OS strategy (13.22%).

At this point the user selects the generation that they believe has hit the best combination of IS and OS performance. In this study, generation 13 was selected. FBPro then allows the user to export all the top 10 strategies that have been found up through that generation for further study. Selecting among the top 10 for the actual strategy to trade is something of a judgement call. Perhaps the investor is willing to give up some return for an improved MDD, or perhaps more

emphasis is placed on how the strategy performed in the OS date range. Sometimes the different strategy results are very similar, and in other instances there can be significant variation. FBPro has an option during optimization to encourage diversity in strategy options and parameters.

FBPro generates a number of statistics for each strategy and builds equity curves for each strategy that can be loaded into the FastTrack charting program. As mentioned, the top 10 strategies will have similar performance, but there can be significant variations. For example, here are four examples of equity curves from the top 10 strategies found by generation 13. Notice that three equity curves are very similar but one (yellow) is quite different:

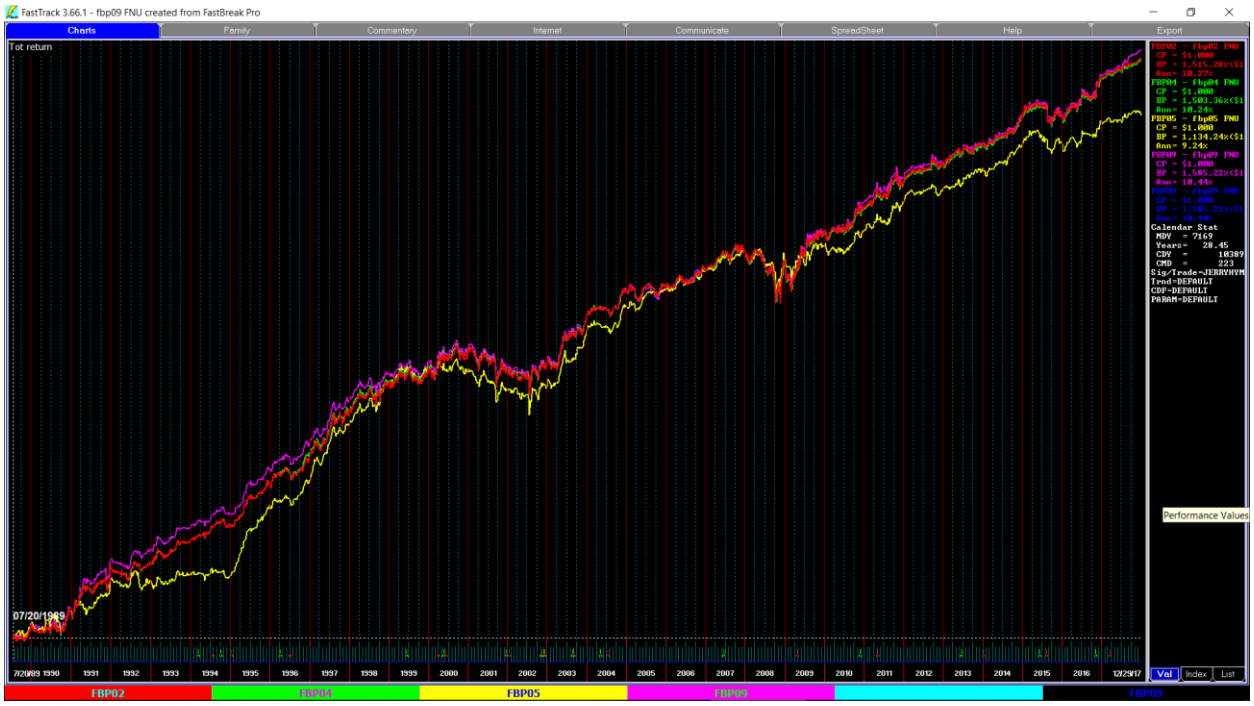

Chart 3 – Selection of Equity Curves from Top 10 Strategies

The FastTrack spreadsheet can also be used to evaluate the strategies with a large number of statistics. The following chart shows a few basic performance parameters from the FastTrack spreadsheet for the top 10 strategies (ZIG/S&P):

Strategy	Annual Return, %	Daily MDD, %
1	9.38	-23.67
2	9.19	-23.21
3	10.27	-24.57
4	9.40	-25.35
5	10.24	-24.57
6	9.24	-23.67
7	9.43	-23.72
8	9.10	-23.56
9	8.92	-22.80
10	10.44	-22.60

Table 8 – Performance Results for Top 10 Strategies

We selected strategy 10 because of its somewhat better performance in both the IS and OS date ranges. The strategy is quite active and averages 19 trades per year

Graphically, how does our equity curve look? In the following chart: ZIG strategy by itself (red), VFINX (green) and ZIG combined 50/50 with VFINX (yellow):

Chart 4 –ZIG alone (red), VFINX (green) and 50/50 ZIG/VFINX (yellow)

In the graph we can see the strategy is doing what was hoped for, and that is to provide protection against drawdowns in the S&P, while having good absolute performance.

You may ask, "Why not simply trade the dollar/bond strategy since it has better performance than combining it with VFINX?" A couple responses: A) The above data is mostly optimization data and we certainly would not expect the strategy to perform as well in real-time, B) There are some years when ZIG does better and there are other years when the VFINX performs better - you never know in advance which will do best. This parallels the same logic that many professional money managers use when they recommend a 60/40 equity/bond mix. During some years one class does better than the other, and the bond

allocation helps mitigate drawdowns for the entire portfolio when the stock market declines.

Table 9 shows the year-by-year results with the best gains for each strategy indicated in green and the worst MDD (daily) indicated by red:

Year	VFINX, Ann,%	VFINX MDD,%	ZIG, Ann,%	ZIG MDD,%	ZIG & VFINX, Ann,%	ZIG & VFINX MDD, %
All	9.28	55.26	11.69	21.8	11.26	21.83
1990	-3.32	19.19	21.43	12.06	8.96	6.19
1991	30.28	5.57	24.41	8.37	27.97	5.93
1992	7.45	5.64	3.31	9.44	5.57	4.92
1993	9.9	4.81	13.59	6.69	11.86	4.76
1994	1.18	8.48	13.89	6.51	7.79	4.04
1995	37.69	2.5	15.93	5.79	26.48	2.18
1996	22.72	7.45	2.8	7.47	12.66	5.87
1997	33.31	10.79	19.05	5.95	26.59	6.79
1998	28.71	19.2	-1.38	12.36	13.55	8.28
1999	21.13	11.81	-6.37	12.68	7.23	7.83
2000	-9.1	16.55	25.25	9.74	7.74	7.55
2001	-11.99	29.17	-8.03	11.55	-9.19	16.88
2002	-22.2	33.01	33.65	6.77	3.32	12.21
2003	28.59	13.79	21.77	9.94	26.07	5.24
2004	10.74	7.47	17.55	7.76	14.59	4.9
2005	4.8	7.01	-3.89	14.27	0.68	8.82
2006	15.73	7.47	6.47	7	11.33	4.24
2007	5.37	9.88	11.92	6.09	9.32	6.34
2008	-37.02	47.72	43.48	15.39	-1.51	20.75
2009	26.57	27.17	0.41	10.25	14.31	13.31
2010	14.96	15.66	14.8	7.13	16.03	4.53
2011	1.98	18.69	25.07	14.19	14.93	6.99
2012	15.78	9.6	-1.35	8.76	7.32	5.29
2013	32.28	5.6	-3.03	8.39	13.72	4.26
2014	13.55	7.3	16.01	4.48	15.27	3.01
2015	1.25	12.05	-0.08	14.66	1.23	10.66
2016	11.85	10.29	28.07	8.34	20.44	4.11
2017	21.8	2.6	7.52	3.14	14.57	1.82
2018	-5.37	19.4	13.64	6.93	4.31	7.24

Table 9 – Year by Year Results

There is a good distribution in the "winning years" split between VFINX and the ZIG/VFINX strategy. The number of MDDs are skewed to VFINX, and the VFINX MDDs tend to be substantially greater than ZIG/VFINX MDDs. There is only one year when the combined ZIG/VFNIX has the best result (2010), but that is not unexpected. In no year does the combined strategy have the worst MDD. Again, these are daily calculated MDDs. See Table 1 for the monthly calculated MDD values. The combined ZIG/VFINX strategy only had two losing years: the tech bubble crash year 2001 and a very small loss in 2008. The large gain for ZIG couldn't overcome the even larger loss in VFINX during 2008.

Distribution of Gains among Funds

How are the trading gains and other statistics distributed among the four fund investment choices and the money market fund? The following table from FBPro summarizes statistics on the funds selected by the trading strategy:

Symbol	Name	# of times Purchased	Winning, %	Gain, %	Max, %	Min, %	Avg, %	Ann, %
RYGBX	Rydex Gov Long Bond	115	46.1	111.4	21.9	-6.9	0.97	14.6
RYJUX	Rydex Inverse Gov Bond	92	35.9	21.4	12.7	-4.7	0.23	5.3
RYSDX	Rydex Strengthening Dollar	73	49.3	88.2	21.2	-5.4	1.2	19.3
RYWDX	Rydex Weakening Dollar	80	53.8	120.6	14.4	-6.0	1.5	23.9
VMMXX	Vanguard Money Market	200	100	22.6	1.3	0	0.1	2.7

Table 9 – Statistics on Funds Purchased

The number of times each fund is purchased and the summation of gains (Gain%) is similar for all funds, and no one or two funds dominate. The inverse bond fund is a bit of an exception, but this isn't too surprising because we generally have been in a declining interest rate environment for the entire testing period. Going forward that may or may not be the case. The largest losing trade for each fund hovers around -4% to -7% for all funds. The final column (Ann%) is the average annualized percent gain while invested in the fund.

Options used by the ZIG Strategy

As mentioned earlier, a penalty was used in the optimization process to prevent too many options from being used. The ZIG strategy used more options than we typically like to see in a strategy, but the strategy has been performing well in real-time. Here are the options selected:

Buy Filters Options	Stop Options
Parabolic	Wilder's Parabolic (29%)
Beta[11]	Exponential Moving Average (EMA) (14%)
Rate of Return (ROR)	Harnsburger Option[12] (13%)
Wilder RSI	

Table 10 – Buy Filters and Stops Selected by Optimizer

To make certain that a particular Stop option wasn't used simply to avoid just one or two bad trades; all the trades were examined to see why a position was sold. As noted earlier, the strategy averages 19 trades per year so the total

number of trades exceeds 500 during approximately 30 years of testing. The most common reason (44%) was because a fund lost relative momentum compared to the other funds in the trading family. Simply, a fund was sold when it dropped below the ranking cutoff point and another fund rose in the ranking to take its place. Note the percentages (%) next to the individual Stops in the above list. The Stops came into play by percentages ranging from 13% (Harnsberger) to 29% (Wilder's Parabolic). We were comfortable that we were not "data mining" by selectively using Stop options.

Variations in using ZIG within a Portfolio

Although ZIG was specifically developed in conjunction with hedging the S&P 500 Index, can it be used to hedge holding something other than the S&P 500 Index? The simple answer is yes. You can very quickly try incorporating ZIG with other strategies within FBPro. For example, we used one of the leveraged Rydex S&P 500 Index funds in conjunction with ZIG. The Rydex 2X S&P fund RYTNX has been available since 2000; however, as we did earlier, we can create synthetic data back to 1988. Combining ZIG with RYNTX in a 75%/25% weighting, the combined annual return was improved by approximately 1.75% compared with VFINX in a 50%/50% weighting, and the MDD increased by less than 2%.

Chart 5 (duplication of Chart 1 found in Abstract) displays the equity curve for ZIG only (red), VFINX (green), a 50%/50% weighting between ZIG and the VFINX (yellow), a 75%/25% weighting between ZIG and a 2x leveraged S&P 500 Index fund (blue):

Chart 5 - Equity Curves for Combinations of ZIG and Other Idexes or Funds

Table 11 (duplication of Table 1 found in Abstract) summarizes the results in tabular form:

Symbol	Strategy	Annualized, %	Daily MDD, %	Monthly MDD, %	Correlation, %	Beta
VFINX	Buy & Hold	9.29	-55.26	-51.0	100.00	1
ZIG	ZIG only	11.69	-21.79	-18.9	-17.45	-0.13
ZIG/VFINX	50%/50%	11.27	-21.83	-14.0	75.52	0.43
ZIG/2xS&P	75%/25%	13.03	-23.54	-17.4	57.88	0.40

Table 11 - ZIG Performance (7/20/1989 – 12/31/2018)

Effect of Rebalancing on a Monthly or Quarterly Basis

The study was conducted with daily rebalancing between ZIG and VFINX and other potential funds. FastTrack has the capability to rebalance equity curves on a user defined basis. Chart 6 shows the effect on the equity curves if ZIG and VFINX are rebalanced on a daily (red), monthly (green) or quarterly (yellow) basis:

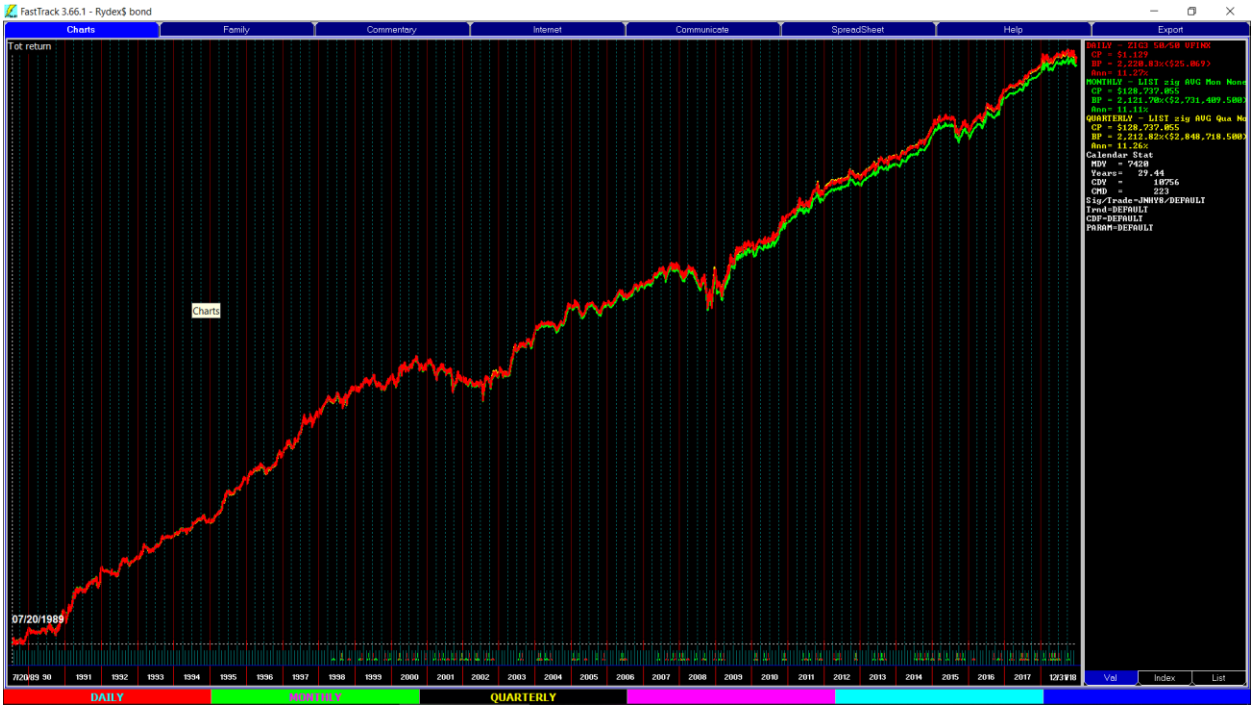

Chart 6 – Effect of Rebalancing: Daily, Monthly, and Quarterly

The rebalancing duration has a very small effect on annual return: Daily (11.27%), Monthly (11.11%), and Quarterly (11.26%)

Future Study

To add flexibility to where a ZIG type of strategy could be traded it would be beneficial to trade the strategy using ETFs. There are a number of government

bonds ETFs, e.g., TLT, which may be appropriate. There are more limited choices on inverse bond funds but TBT is a possibility. Currency funds are more problematic. UUP and UDN are ETFs that are long/short the Dollar Index (DXY) but they are unleveraged funds – the Rydex funds used in the study are 2X leveraged. URR and DRR are 2x leveraged long/short the Euro, and the DXY is highly weighted to the Euro, so perhaps they could be used as the currency funds.

Summary

There are a variety of methods to protect a portfolio during market declines, including market timing, diversification with bonds, etc. All methods have their drawbacks. The ZIG strategy uses funds that have proven to have low and even negative correlation with the S&P 500 Index, and the strategy has been tested on thirty years of data, including a year of real-time performance in the very stressful 2018 market conditions, and has so far proven to be robust.

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[1] Bogle, John C. ,*The Little Book of Common Sense Investing*, (New Jersey: John Wiley & Sons, Inc. 2nd edition, 2017) Note: This paper was being written just days after the death of John Bogle, who is legendary for promoting the idea of buying and holding low cost index funds.

[2] The historical data used in this study comes from Investors FastTrack (www.investorsfasttrack.com/) which has a very extensive end-of-day stock and mutual fund database that is adjusted for dividends and splits. The beginning date of their database is 9/1/1988.

[3] The Correlation and Beta values throughout the paper were calculated using the Investors FastTrack spreadsheet. FastTrack calculates correlation as a percentage rather than as a fraction, and that format was retained for this report.

[4] Beta is of questionable meaning when correlation is low or negative. These values are from the Investors FastTrack spreadsheet.

[5] FastBreak Pro is a product of Edge Ware, Inc. www.edge-ware.com FastBreak Pro was first released in 2000 and has been extensively modified over the years. The application is tightly integrated with the Investors FastTrack database. See manuals for detailed information: https://www.edge-ware.com/FastBreak%20Standard6.5.pdf and https://www.edge-ware.com/FastBreak%20Pro6.5.pdf

[6] All charts in this paper use the Investors FastTrack charting program and are log/normal.

[7] Pardo, Robert, *Design, Testing, and Optimization of Trading Systems*, 1992, and *The Evaluation and Optimization of Trading Strategies,* 2nd Edition 2008, New Jersey: John Wiley & Sons, Inc.

[8] IBID

[9] IBID

[10] IBID

[11] FastBreakPro allows the user to filter on traditional beta or "non-correlated beta" - which is simply the ratio of standard deviations of a fund and an index. Since the study uses funds with low and even negative correlation, the non-correlated beta filter was used with the S&P 500 as the index.

[12] Harnsberger Option, named after technician Frederick "Fritz" Harnsberger, sells a fund when a different fund is ranked higher than the fund currently held. This is true even when the held fund is ranked above the "cut off" point in the Sell ranking.