

Cross Correlation Case Studies #1 & #2

USAGX (precious metals) as a leading indicator for the S&P 500
S&P 400 (Midcaps) as a leading indicator for the NIKKEI 225

Introduction

This paper discusses methods, presently limited to those readily implementable using Excel spreadsheets, to identify leading indicators for securities trading from cross-correlations between sets of time-series data. It also explores how to quantify the financial returns that might be achieved from leading-indicator-based trading.

In the general case, it is not known a priori whether a time series will be an indicator or a traded security. For instance, one security may be a good leading indicator for another security. This paper shows a method for processing a set of 20 time series, resulting in $20 \times 20 = 400$ cross-correlations, and then presenting the results efficiently for review. The input datasets used here were chosen to be diverse and illustrative, and are not meant to rigorously cover the investment/indicator space.

Cross-correlation calculations produce an output time series that shows the degree of correlation between two input time series as the first time series is sequentially stepped past the second time series. Peaks in this output time series, which can be positive or negative, correspond to leading or lagging intervals where the skewed pair of time series correlate well. The X value of the peak is the lead (or lag) interval, while the Y value is the degree of correlation.

Once a leading indicator is identified, validated, and qualified, there are a variety of ways that it might be incorporated into a trading system to produce profits – each way potentially yielding a different financial performance. The breadth of possibilities and potential outcomes are discussed.

Optimal Prediction Interval

Price predictions have the following attributes:

What is predicted
Price value (quantitative numeric)
Just direction of price change (up/down/stable)
Direction (up/down) with strata of change magnitude (none, small, medium, large)
When prediction is for
A fixed point forward in time
All points from now until a fixed point forward in time

Prediction update interval
Continuously – new predictions are available as fast as one is trying to trade
Sparse – data source forming prediction is updated regularly but slower than desired trading interval
Sporadic – asynchronous events (such as news) trigger a prediction

Uncertainty
Standard deviation and distribution for single point prediction
Error band curves when prediction is a curve

To determine the optimal point in the future (i.e. day, week, month, or year) at which to predict, it is useful to evaluate the maximum theoretical returns versus the trading interval. For simplicity, let us assume that our leading indicator produces 100% accurate projections of price movement direction for a specific (i.e. day, week, month, or year) fixed point forward in the future, and does so continuously, so we always have an up-to-date projection to work from.

Ideally one wants to full-wave rectify the price-versus-time waveform about its mean, extracting profit from every movement up (by holding a long position in the security) and every movement down (with a short position). This requires the prediction interval to be equal to or shorter than the interval of the price fluctuations one is trying to profit from.

It is illustrative to look at a small cross-section of securities – a stock market index (S&P 500), a blue-chip stock (IBM), and a volatile tech stock (Vitesse), and backtest to see the returns one could have achieved from an accurate projection and trading interval of one day, one week, one month, and one year. Table 1 summarizes these results. The investment return multiples shown assume that there is no spread or commission on trades, and that all funds are either in a long position (if the security is forecasted to go up) or a short position (if the security is forecasted to go down) over the next corresponding period (day, week, month, or year), no leverage, and that all transactions are made at the closing price for that period.

Year	S&P500				IBM				VTSS			
	Daily	Weekly	Monthly	Yearly	Daily	Weekly	Monthly	Yearly	Daily	Weekly	Monthly	Yearly
2009	23 X	4.1 X	1.94 X	1.30 X	21 X	3.5 X	1.64 X	1.36 X	146,240 X	264 X	5.21 X	1.33 X
2008	82 X	5.4 X	1.90 X	1.67 X	74 X	7.2 X	2.32 X	1.15 X	46,079 X	309 X	11.6 X	2.08 X
2007	6.1 X	2.3 X	1.33 X	1.04 X	11 X	3.5 X	1.63 X	1.10 X	94 X	10.5 X	2.85 X	1.13 X
2006	3.3 X	1.8 X	1.21 X	1.12 X	5.5 X	2.2 X	1.43 X	1.24 X	5,176 X	62.9 X	14.5 X	3.06 X
2005	3.7 X	1.8 X	1.25 X	1.08 X	6.9 X	3.0 X	1.86 X	1.14 X	403 X	16.4 X	5.65 X	1.12 X
2004	3.9 X	1.8 X	1.25 X	1.04 X	6.1 X	2.3 X	1.47 X	1.05 X	3,095 X	52.9 X	10.6 X	2.84 X
2003	8.1 X	2.3 X	1.42 X	1.32 X	16 X	3.7 X	1.42 X	1.28 X	4,665 X	62.6 X	6.09 X	3.99 X
2002	24 X	3.2 X	1.87 X	1.32 X	148 X	11.5 X	4.47 X	1.37 X	6,246,288 X	922 X	274 X	6.11 X
2001	13 X	3.3 X	1.75 X	1.21 X	68 X	6.3 X	3.13 X	1.03 X	2,018,153 X	2,394 X	38 X	5.62 X
2000	15 X	3.6 X	1.59 X	1.02 X	323 X	9.9 X	2.75 X	1.00 X	896,619 X	372 X	42 X	1.63 X
1999	10 X	2.9 X	1.54 X	1.09 X	117 X	8.3 X	2.39 X	1.23 X	3,398 X	17.7 X	4.02 X	1.68 X

Maximum theoretically achievable ending / starting value per year, based on given trade frequency, capturing all upward motion on long trades & all downward motion on short trades.

Table 1

From the table it can be seen that under these ideal conditions, the faster one trades the better the returns, presuming the price movement prediction remains accurate. Thus the optimal trading period is the same as the minimal time in the future for which one consistently has accurate forecasts. There are dramatic gains (averaging over 5X more) in all of the securities evaluated if one can accurately predict the direction of the next day's price movement, versus predicting the next week's price movement.

Visualization – Cross Correlation of Price Histories

The test cases themselves form a 2-dimensional matrix, and the cross correlation results can be reduced to 2 relevant numbers (lead interval and degree of correlation), resulting in 4 dimensions that need to be conveyed to the analyst. Two ways to present this information are shown here.

The first method, as seen in Figure 1, is to make a table of the individual cross-correlation graphs. Excel has a feature called “Sparklines” which facilitates this. Each of these graphs covers the range of 1 to 100 trading days of leading skew, as shown in the key. On the diagonal where a time series is cross correlated with itself (autocorrelation), the background is grey. A pronounced peak in the graph indicates that the time series in the left column may be a good leading indicator for the corresponding time series shown in the top row. How much the peak is shifted to the right gives the amount of lead.

The second method is shown in Figure 2. Here 2 pieces of information are coded into each cell of the table: the peak (positive or negative) leading cross correlation, and whether it is leading in an interval of particular interest (1 to 70 trading days was chosen).

The value of the leading cross correlation peak appears as the number in each table cell and also as a bar graph within the cell. If the cross correlation was not leading, then the cell is blank. Excel calls these in-cell bar graphs “Data Bars”. The way to review this is to look for cells with a colored background that also contain a large blue or purple data bar, corresponding to high cross correlation with a leading peak in the target range.

From either of these visualizations one can see the relationship noted prior to this paper, that the precious metals ETF USAGX is a 65 trading day leading indicator for the S&P 500 and other stock indices. It shows relatively high correlation (0.6 to 0.8, depending on the stock index) with a peak that is offset to the right from the Y axis (which is just off the left edge of each Sparkline). It is granted that this cross correlation is just based on 2 years and 8 months of data, and thus may not hold in general.

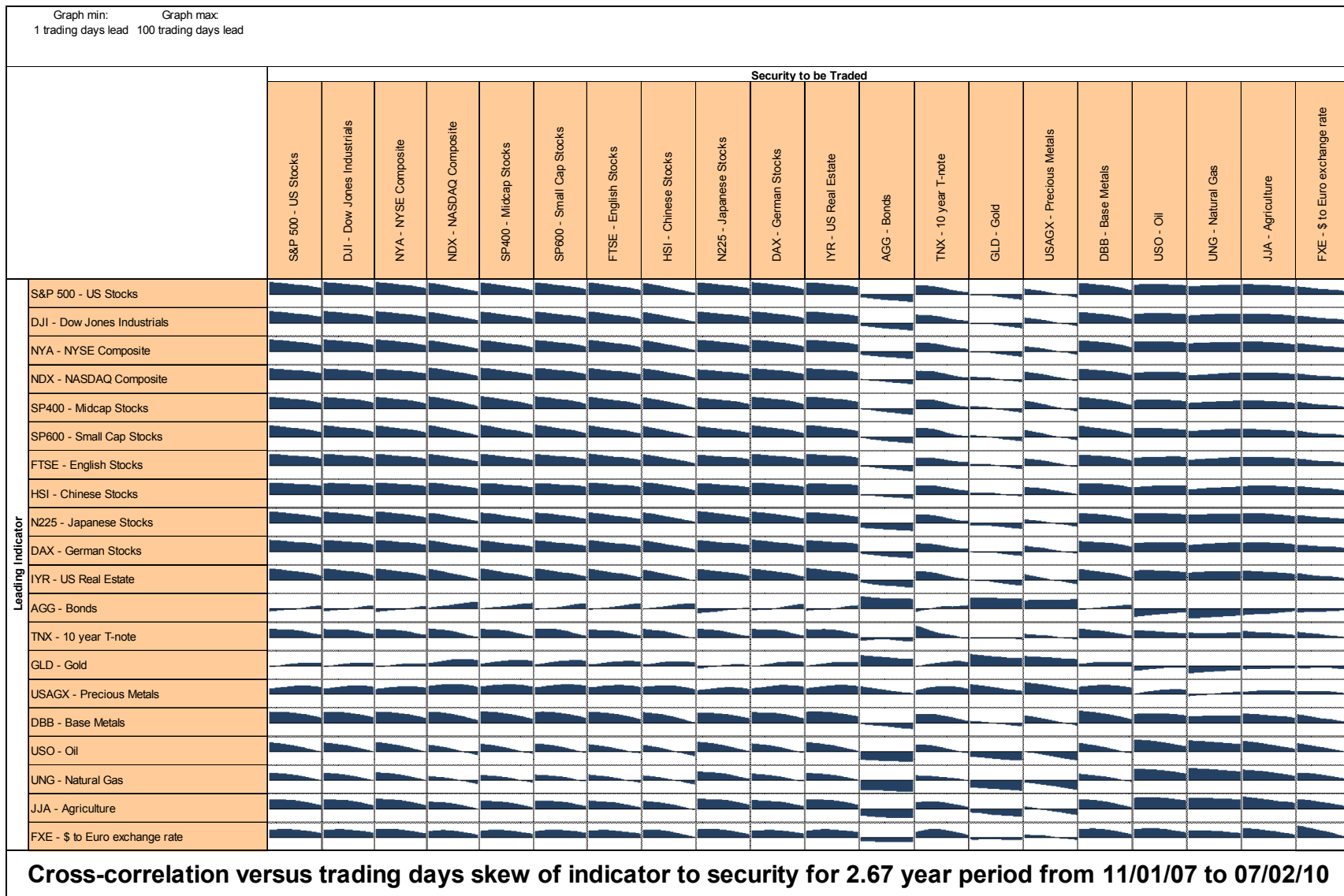


Figure 1

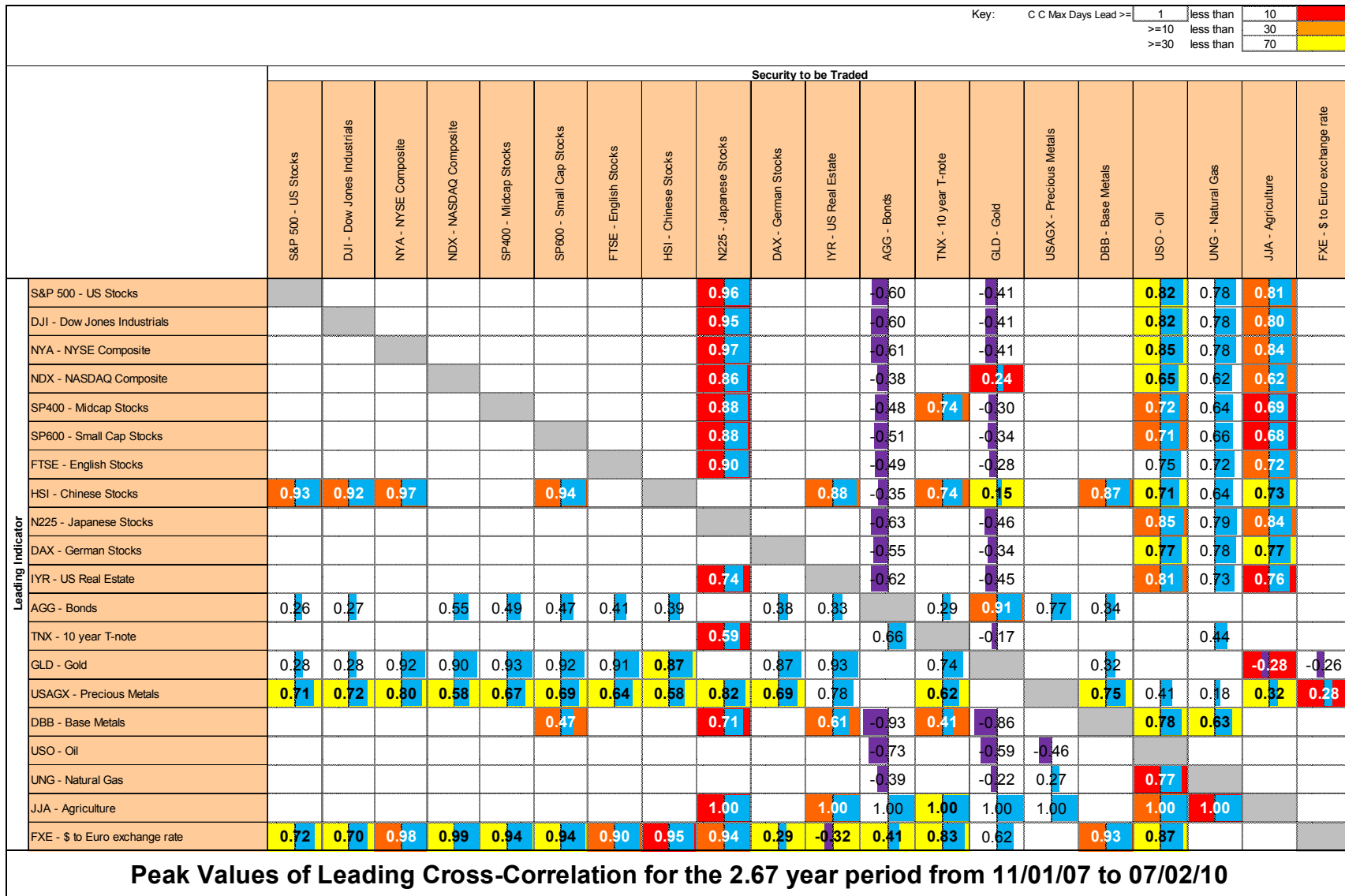
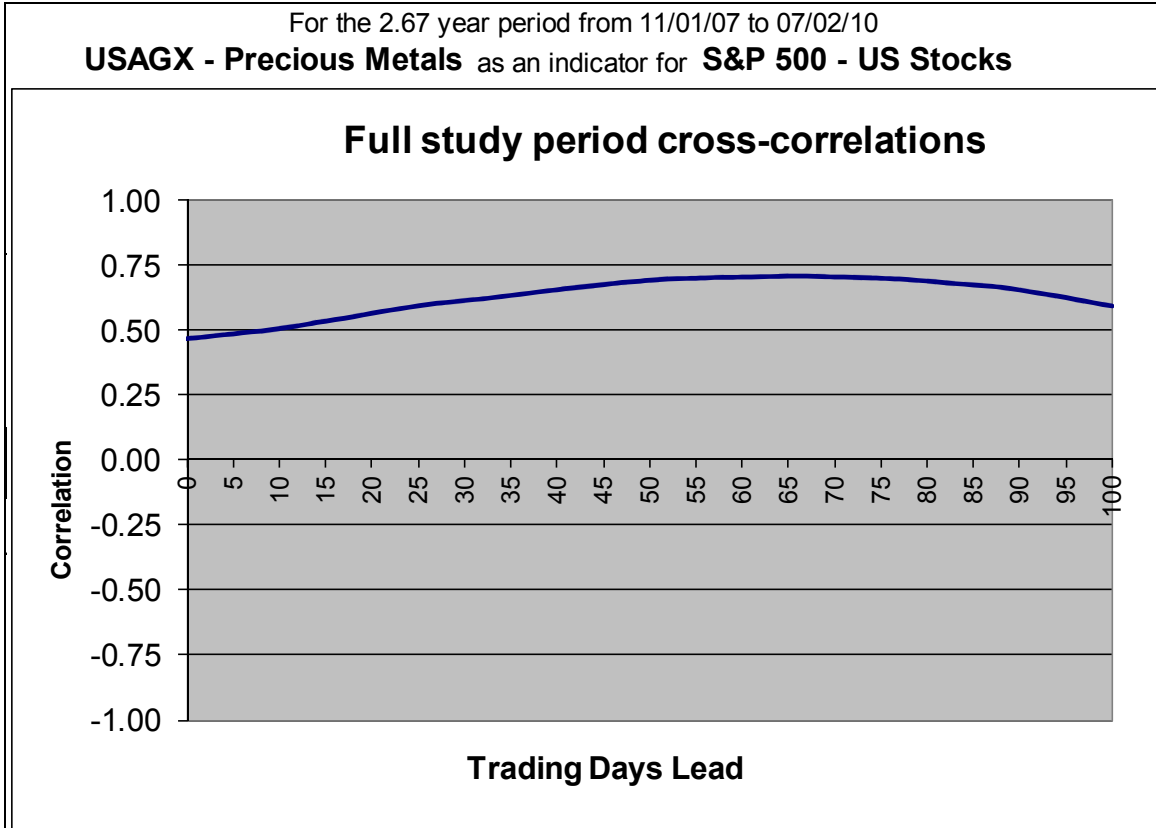


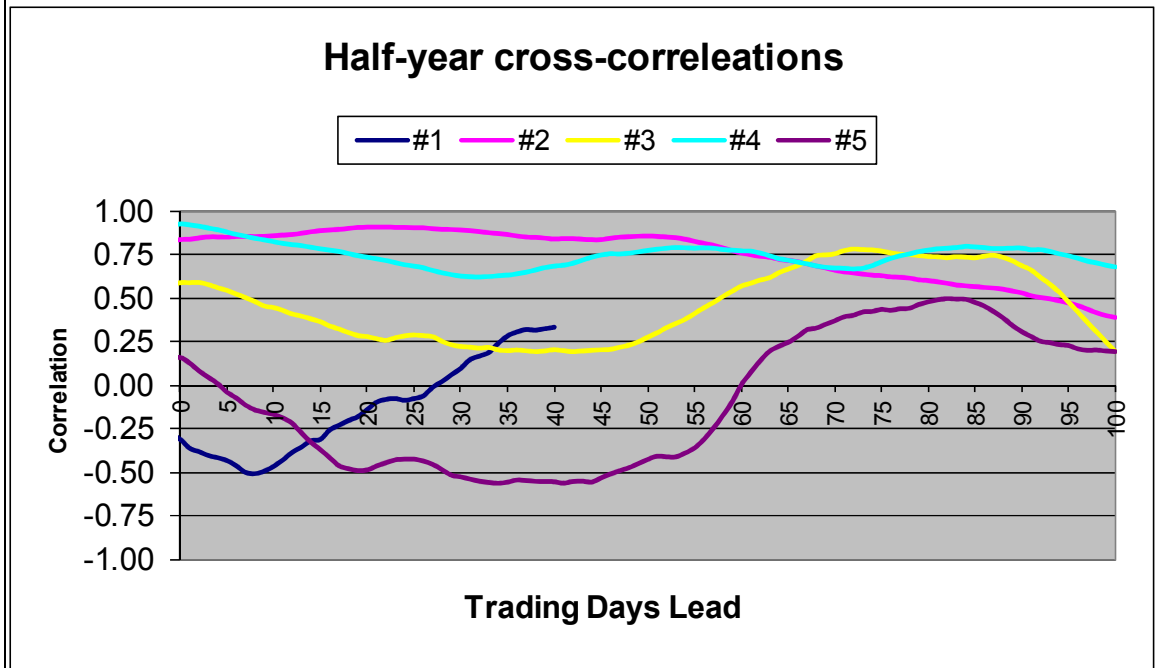
Figure 2

Let's set validation of USAGX as a leading indicator for stock indices in the long term aside for now, and just look further into quantifying its significance assuming it did pass muster.

The upper half of Figure 3 shows an enlarged curve of the cross-correlation of USAGX with the S&P 500 over the full study period. The lower half dissects this to look at adjacent $\frac{1}{2}$ year segments to see how consistent the peak is over time. The curve for half year #1 doesn't extend out to the peak region (between 60 to 95 days lead) because this corresponds to datapoints that are outside of the dataset analyzed. Of note is that odd half years #3 and #5 showed strong peaking, while even half years #2 and #4 were flatter. So there may be an annual periodicity to the cross correlation.



Full period cross-correlation peak at 65 trading days (= 13.0 weeks, or 3.1 months).



Half-year cross-correlation peaks: #1: +8, #2: +22, #3: +72, #4: 0, #5: +34 trading days.

Figure 3

Figure 4 shows the two datasets, normalized to be at the same scale. It is evident that the major movements of the S&P are predated by 3 to 4 months by comparable movements in USAGX, as shown by the curved arrows.

In Figure 5 the overlaid USAGX curve is shifted forward by 65 days. This shows more clearly how well and not-so-well it predicts the behavior of the S&P 500. Two regions are blown up further in the lower portion of Figure 5. A conclusion is that at the (presumable optimal) fixed time shift chosen, USAGX is not a good predictor of the S&P 500 movements in the less-than-1-month time frame.

Given the types of insights that this type of prediction yields, and what it doesn't give, the next question is how to monetize this.

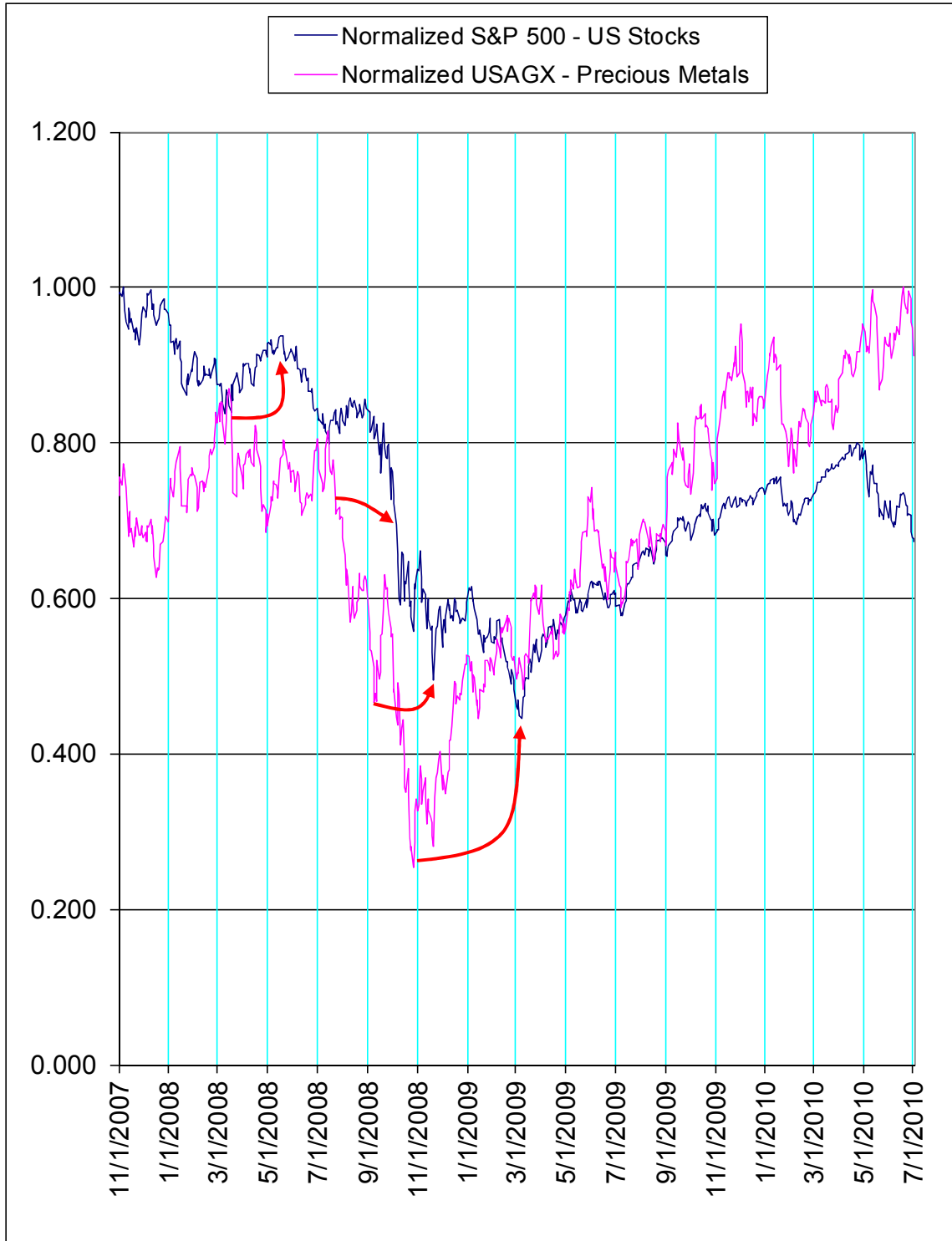


Figure 4

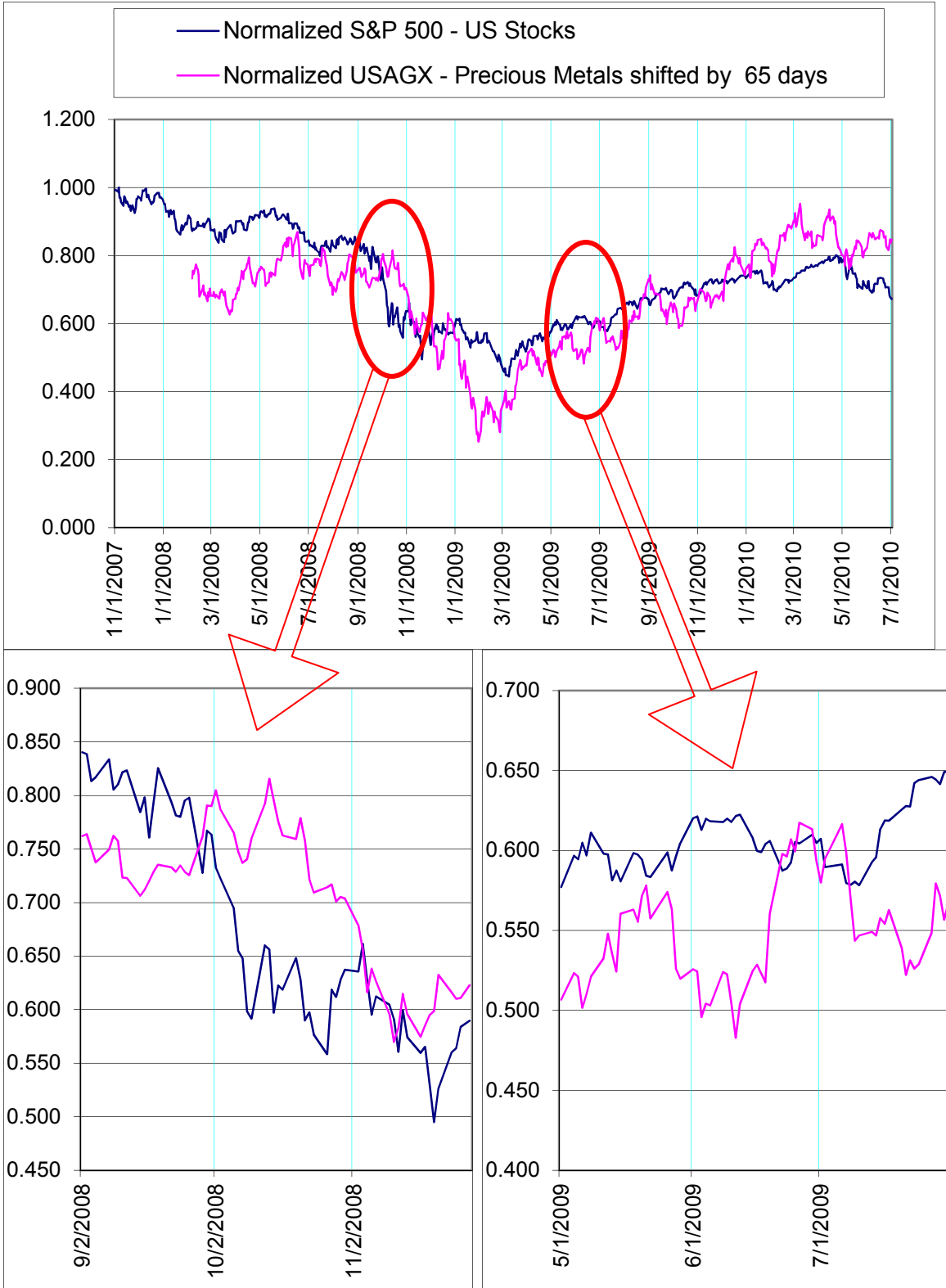


Figure 5

Monetization of Cross-Correlated Price Histories

For high financial returns, we are interested in trading items with a high ratio of {change in value divided by time}, coupled with good predictability. If the mechanism of investing in the security is either by buying it long or selling it short (with inconsequential commission and spread), then our predictability needs to be only on the direction of price movement (thus whether we take a long or short position in the security), not the magnitude of the change.

The characteristics of USAGX predicting the S&P 500 are: price value from now until 2 to 4 months hence, updated continuously, with as-of-yet unquantified accuracy. Here are a set of possible ways to capitalize on such a prediction, given that USAGX leads the S&P 500 on average by 65 trading days:

Investment vehicle	Methodology
Long or short position in S&P 500 component stocks or an S&P 500 index ETF	Generate buy long / sell short signals for S&P 500 from a 65 trading day simple moving average (SMA) on the USAGX crossing a 1 year SMA on the USAGX. The inherent SMA delay of trading signals should align buy/sell transactions with S&P 500 peaks and valleys.
Put and call options	<p>If USAGX made a big move (>10%) up over the previous 2 months, buy a 2 month call option on the S&P 500 (since the S&P is projected to repeat this within 2 to 4 months from the USAGX move). Exercise the option if it is in-the-money at expiration, or earlier if the S&P 500 reaches 75% of the rise seen previously on the USAGX.</p> <p>If USAGX made a big move (>10%) down over the previous 2 months, buy a 2 month put option on the S&P 500. Exercise the option if it is in-the-money at expiration, or earlier if the S&P 500 reaches 75% of the drop seen previously on the USAGX.</p> <p>If USAGX changed less than 10% over the last 2 months, then don't take any positions.</p>
Others?	

A new spreadsheet, “Leading Indicator Performance - USAGX SP500”, was written to evaluate trading returns using various trading models. The first strategy, to use moving averages on the USAGX to trigger long and short positions on the S&P 500, did not yield great results. Performance was calculated over 5+ years of trading, from 9/2005 through 12/2010. Using the default settings of the lead interval for the short moving average, and 1 year for the long moving average, gave 14.3% annual return (CAGR, or Compound Annual Growth Rate), as shown in Figure 6.

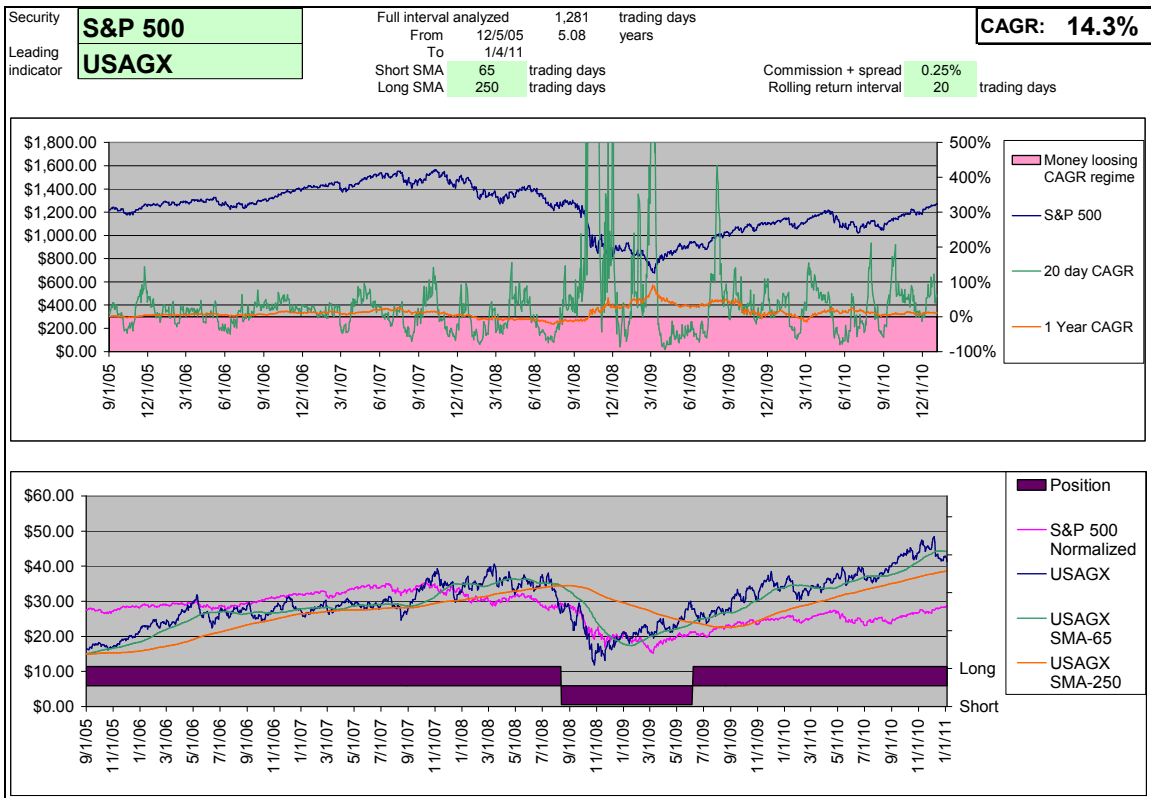


Figure 6

Optimal SMA lengths over the full sample interval were found, as shown in Figure 7, resulting in improved performance, as detailed in Figure 8.

		Long SMA					
		120	130	140	150	160	170
Short SMA	15	11%	13%	16%	17%	19%	18%
	20	11%	11%	16%	22%	22%	19%
	25	13%	19%	20%	23%	22%	19%
	30	13%	16%	19%	25%	20%	22%
	35	14%	17%	23%	29%	19%	21%
	40	11%	17%	21%	22%	21%	20%
	45	14%	20%	24%	25%	24%	21%
	50	14%	18%	24%	21%	20%	24%
		Full-Interval CAGR					

Figure 7

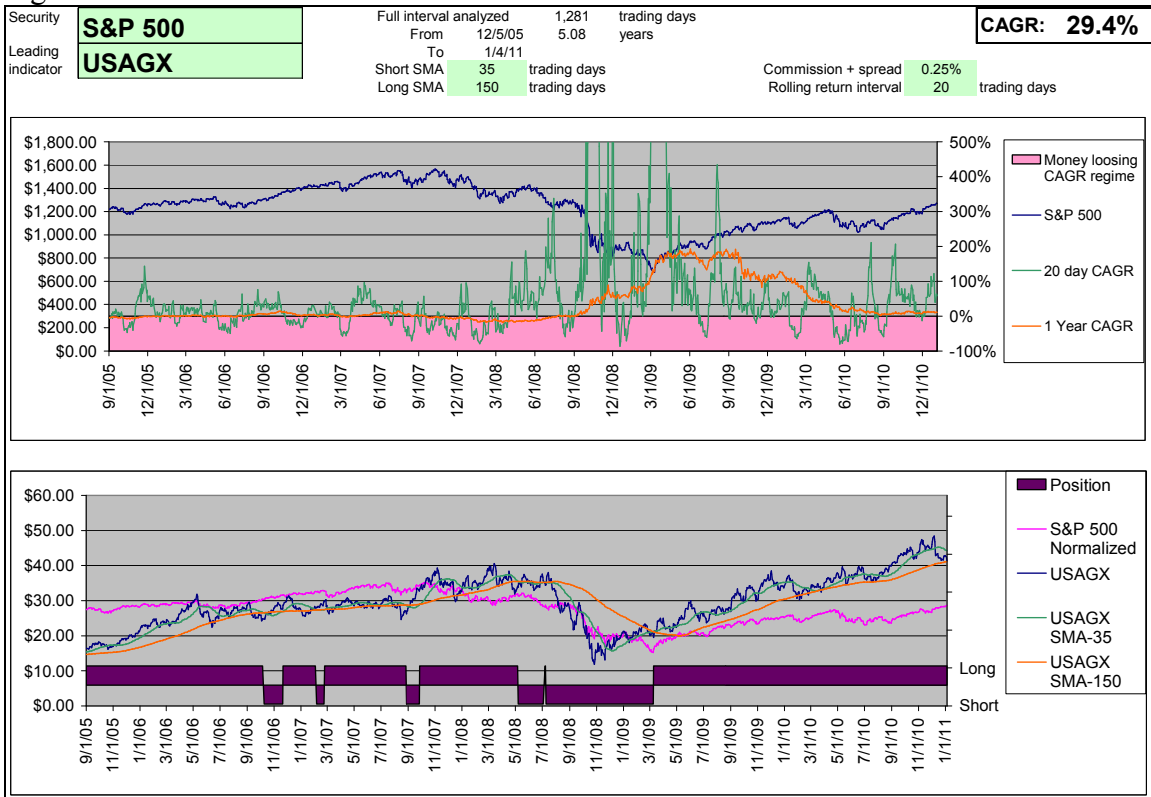


Figure 8

However, just using this same optimized simple moving average strategy with the S&P 500 as the predictor for itself instead of the USAGX yielded a 17% annual return, as shown in Figure 9.

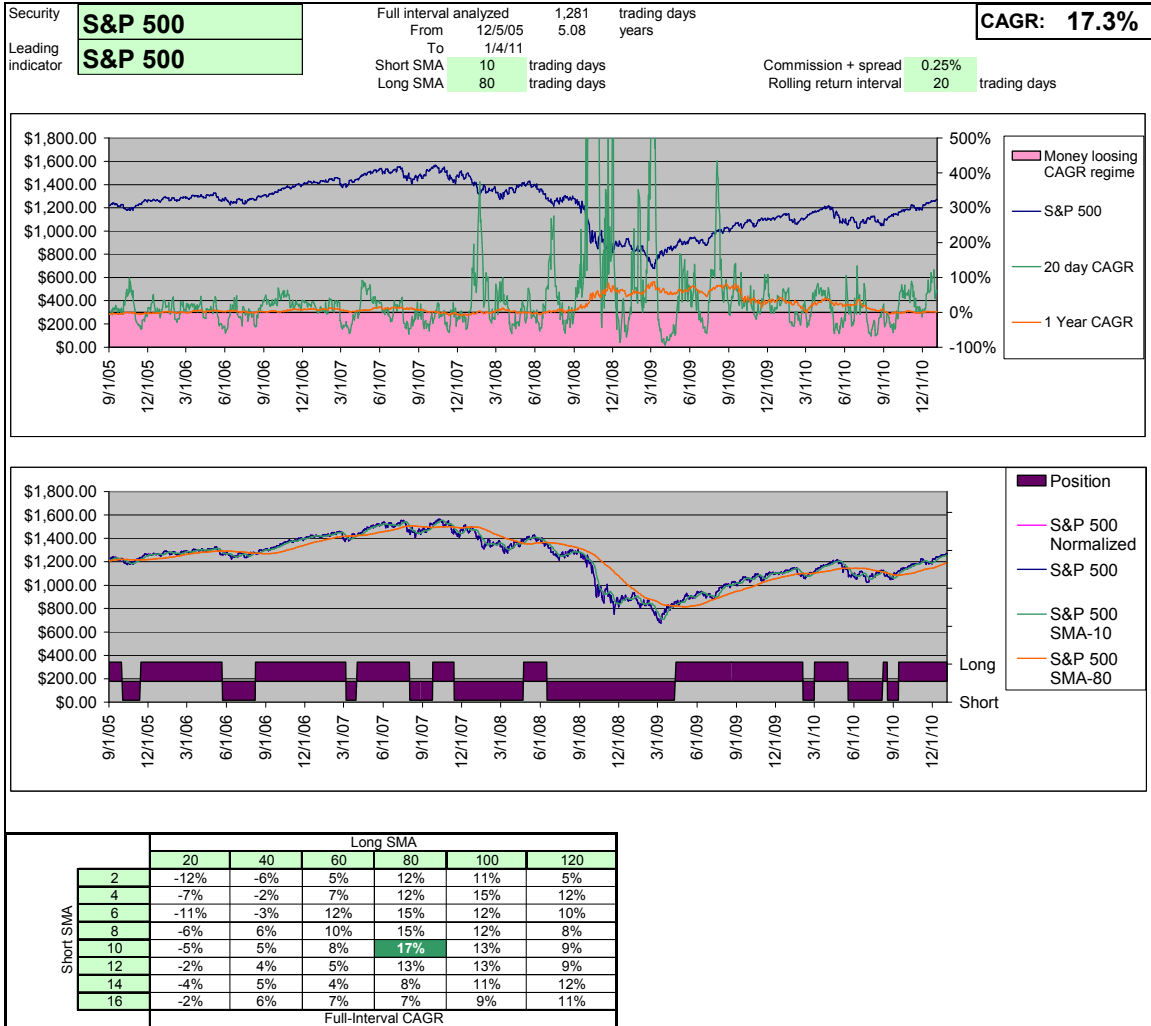


Figure 9

So this trading strategy does not do a particularly good job of capturing value from USAGX predicting the S&P 500.

The put and call strategy over the same 5+ year period from 9/2005 through 12/2010 fared even worse. The assumptions were that each contract was struck at 0.5% out of the money and cost a 6% option premium for a 2 month option expiration, thus the S&P 500 would need to move in the predicted direction by at least 6.5% within 2 months for an option to turn a profit. In the model, 2 contracts could be running concurrently, where the 2nd contract could be entered into 1 month after the 1st contract started. For any contract to start, the leading indicator, USAGX, needed to move by $\pm 10\%$ (the threshold amount) or more in the previous 2 months.

Figure 10 shows the results from this strategy. The “1 Year CAGR” plot shows that there was a region between 10/2008 and 10/2009 where the strategy was making money most

of the time, but overall for the test period it lost practically all of the principal (\$1,000 became \$0.72 in 5 years).

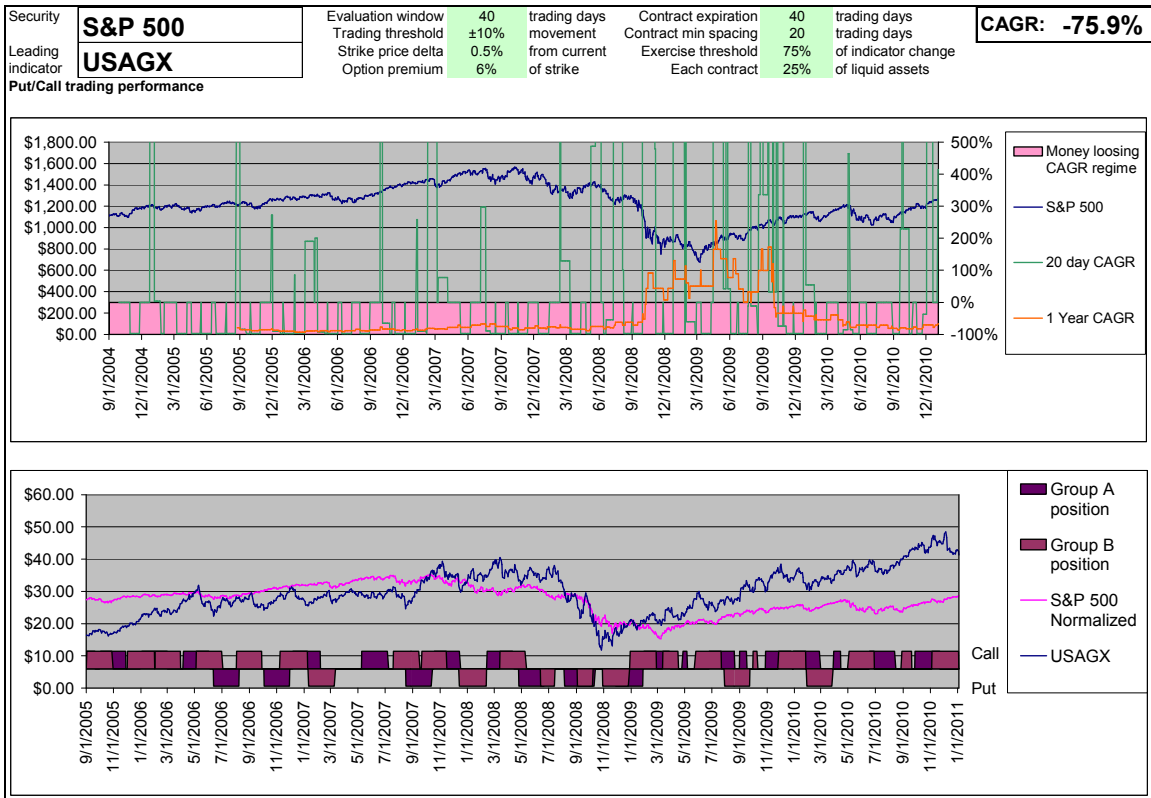


Figure 10

The leading indicator USAGX predicted the S&P 500 movement direction correctly a reasonable amount of the time, per Figure 11; however the 6.5% movement before one could turn a profit caused many of the correct direction predictions to still be unprofitable.

Summary		
	Count	% correct direction
Call contracts	37	59%
Put contracts	17	53%

Figure 11

If put and call contracts can be entered with better terms, then the investment return improves accordingly. At a 2.5% option premium, this strategy is break-even, while at a 1.5% option premium the return skyrockets to 220% per year.

Visualization – Cross Correlation of Price Direction Histories

One can process potential indicators and security price time series before calculating the cross correlation. Here is a listing of some processing operations that may produce useful results:

Type of processing
Slope sign – is it rising, falling, or stable (per some window)
Slope magnitude thresholds – map into bins, linearly spaced or otherwise
Smoothing – such as simple or exponential moving averages, etc.
Technical indicators beyond smoothing – Directional Moving Indicator (DMI), Moving Average Convergence/Divergence (MACD), Stochastics, Relative Strength Index (RSI), etc.
Logical operations – Condition A <AND NOT> Condition B, etc.

The simplest case, slope sign with zero window for stable, run on the same datasets as before, yielded some interesting results. This processing converts a dataset to a series of +1's (for rising or stable price) and -1's (for falling prices). When these processed datasets are cross correlated, we no longer have the case from before of a cross correlation curve with a very shallow peak. Thus it helps to change the scaling and thresholds on how we visualize the data.

Figure 12 shows the cross correlation curves matrix, just over the time scale of 1 to 10 days leading. Most of the relationships just show noise, but, notably, the US and European stock indices show a strong peak at 1 day lead as indicators for the Asian stock indices. The highest cross-correlation is achieved by the S&P 400 (midcaps on the NYSE and NASDAQ) predicting the NIKKEI 225 (whose constituent stocks trade on the Tokyo Stock Exchange). There are weaker cross correlations between the European and US stock indices.

This relationship makes sense, as the sentiment of the much larger US exchanges (\$16.7T capitalization vs. \$8.9T for the Asian exchanges) gets partially carried to the next trading session of the Asian exchanges. The Tokyo Stock Exchange, for instance, opens at 9:00 PM eastern time and closes at 3 AM eastern time; thus there is no overlap with Wall Street's normal trading hours.

Figure 13 shows the tabulated visualization of this data, with highlighting thresholds now set at 1, 2, and 3 weeks lead (5, 10, and 15 trading days), and beginning at 1 day.

Figure 14 shows the cross correlation in more detail, including its consistency across each of the five ½ year periods analyzed.

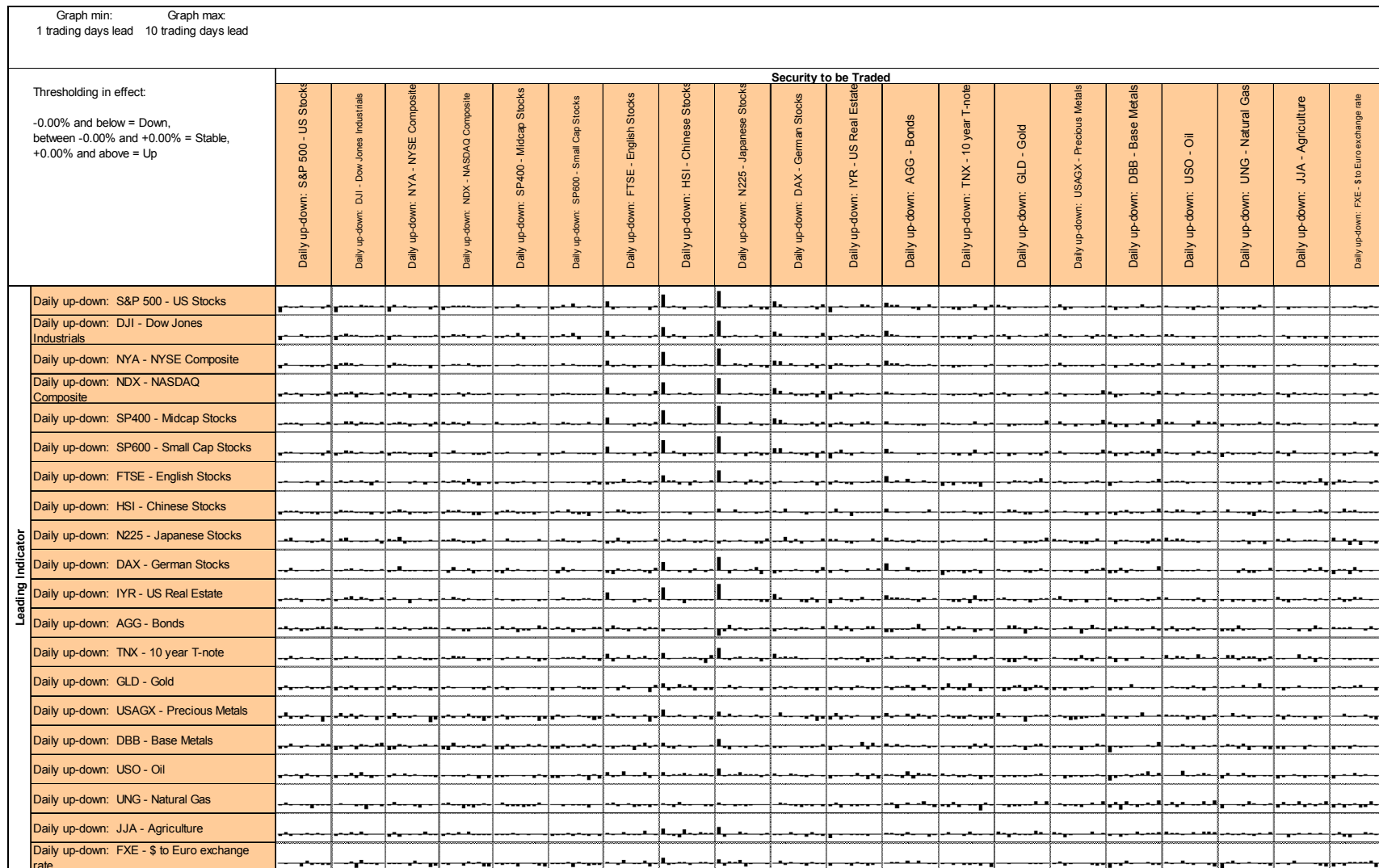


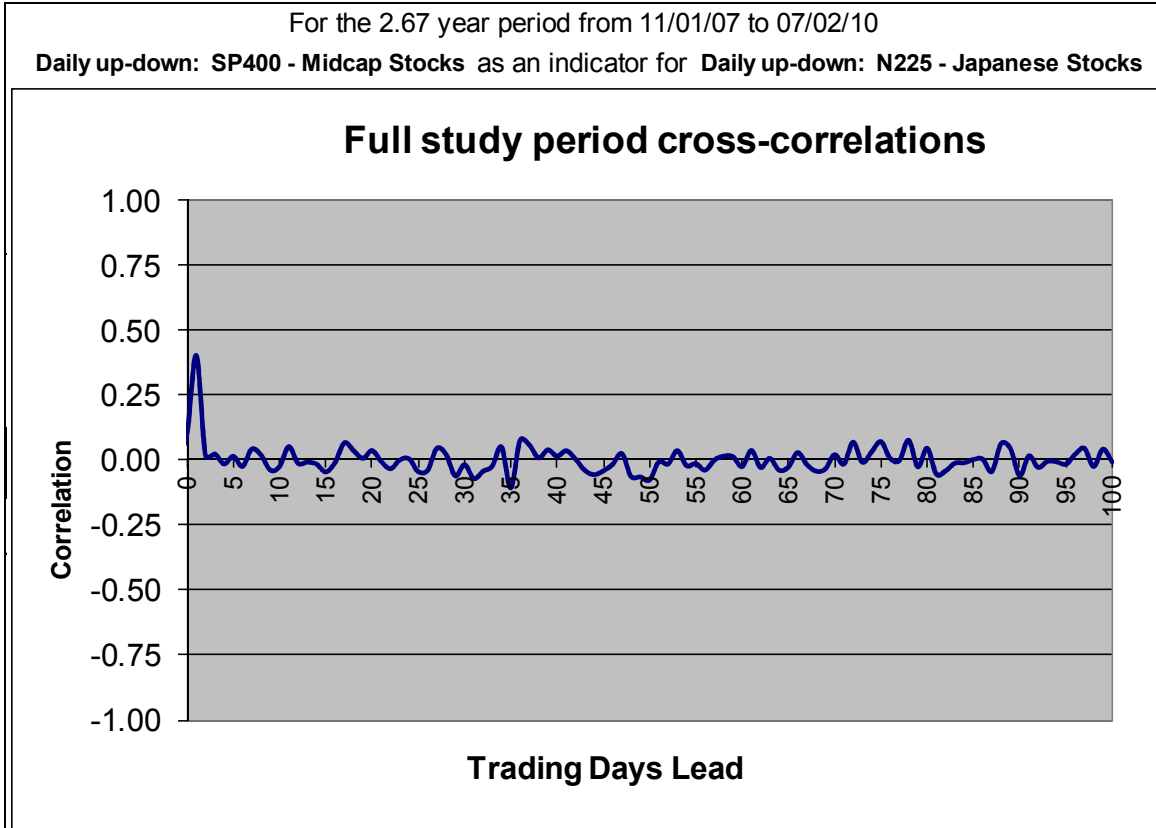
Figure 12

Cross Correlation
Case Studies #1 & #2

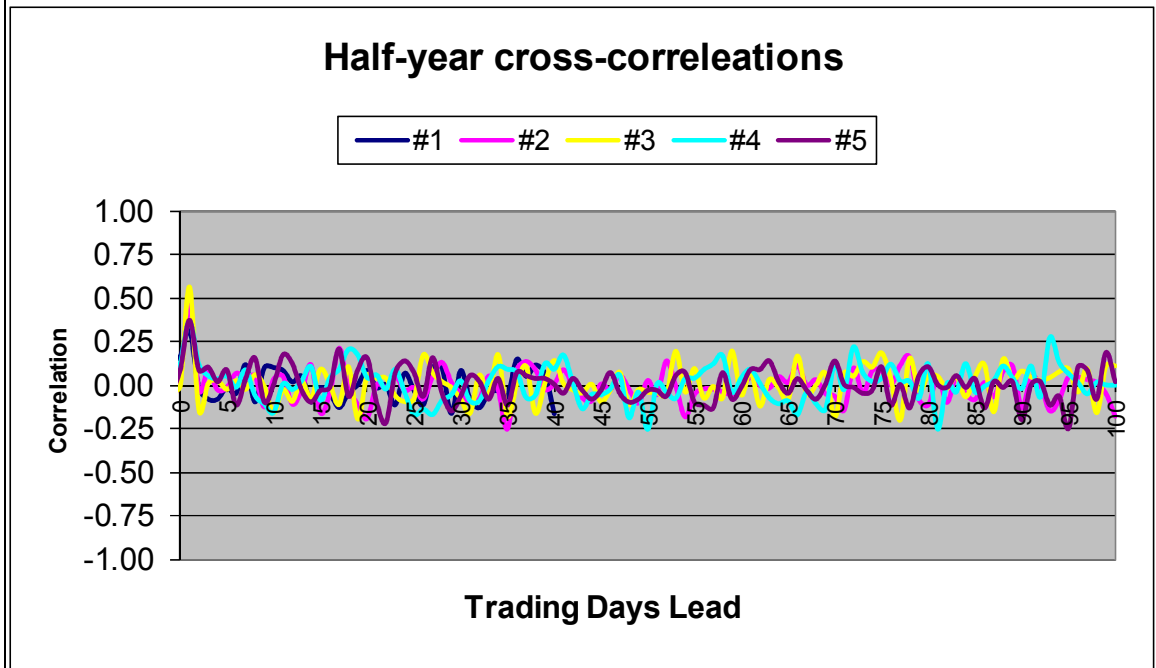
		Security to be Traded																			
Thresholding in effect: -0.00% and below = Down, between -0.00% and +0.00% = Stable, +0.00% and above = Up		Daily up-down: S&P 500 - US Stocks	Daily up-down: DJI - Dow Jones Industrials	Daily up-down: NYA - NYSE Composite	Daily up-down: NDX - NASDAQ Composite	Daily up-down: SP400 - Midcap Stocks	Daily up-down: SP600 - Small Cap Stocks	Daily up-down: FTSE - English Stocks	Daily up-down: HSI - Chinese Stocks	Daily up-down: N225 - Japanese Stocks	Daily up-down: DAX - German Stocks	Daily up-down: IYR - US Real Estate	Daily up-down: AGG - Bonds	Daily up-down: TNX - 10 year T-note	Daily up-down: GLD - Gold	Daily up-down: USAGX - Precious Metals	Daily up-down: DBB - Base Metals	Daily up-down: USO - Oil	Daily up-down: UNG - Natural Gas	Daily up-down: JJA - Agriculture	Daily up-down: FXE - \$ to Euro exchange rate
Leading Indicator	Daily up-down: S&P 500 - US Stocks							0.27	0.36						0.11				-0.09		
	Daily up-down: DJI - Dow Jones Industrials							0.22	0.35						-0.10				-0.10		
	Daily up-down: NYA - NYSE Composite							0.30	0.39												
	Daily up-down: NDX - NASDAQ Composite							0.28	0.37						0.09				-0.12		
	Daily up-down: SP400 - Midcap Stocks							0.30	0.40												
	Daily up-down: SP600 - Small Cap Stocks							0.28	0.37						-0.13						
	Daily up-down: FTSE - English Stocks									0.28			0.15		0.14				-0.10		
	Daily up-down: HSI - Chinese Stocks						0.37					0.12	-0.09	0.08	0.11				-0.10		
	Daily up-down: N225 - Japanese Stocks	0.13	0.12	0.60	0.59	0.68	0.69					0.17	0.08	-0.10	0.12	0.13		0.13	-0.11	-0.10	0.10
	Daily up-down: DAX - German Stocks									-0.15			0.16		0.12				0.10		
	Daily up-down: IYR - US Real Estate								0.12	0.24					0.10				-0.09		
	Daily up-down: AGG - Bonds								0.10	-0.14					-0.10	0.11	0.14		-0.13	-0.10	0.11
	Daily up-down: TNX - 10 year T-note								0.17	0.11					-0.11	-0.13			-0.10		0.09
	Daily up-down: GLD - Gold	-0.12	-0.12		0.26		0.23	0.34	0.22	0.16	0.31	0.20	-0.11	0.19					0.10		
	Daily up-down: USAGX - Precious Metals								0.18	0.16			0.12	0.18					-0.12		
	Daily up-down: DBB - Base Metals									-0.09			0.10						0.14		
	Daily up-down: USO - Oil									0.15				0.12							
	Daily up-down: UNG - Natural Gas	-0.09	-0.10	0.27	0.16		0.16	0.13	0.13	0.11	0.13	0.13	-0.11	-0.09	0.32	0.35					
	Daily up-down: JJA - Agriculture								1.00	1.00			1.00								
Daily up-down: FXE - \$ to Euro exchange rate								0.30	0.30			0.12	0.60								

Peak Values of Leading Cross-Correlation for the 2.67 year period from 11/01/07 to 07/02/10

Figure 13



If Up/Down, motion threshold = 0.00%, direction prediction 66% correct for 1 trading day ahead.



Half-year cross-correlation peaks: #1: +1, #2: +1, #3: +1, #4: +1, #5: +1 trading days.

Figure 14

In this case the prediction continually yields day-ahead price movement direction information, and nothing significant about price movements anytime thereafter.

So, how do we best monetize this?

Monetization of Cross-Correlated Price Direction Histories

As was just noted, this prediction has different characteristics than the previous one, and likely fewer ways that one can profit from the information. Here are some possibilities:

Investment vehicle	Methodology
Long or short position in NIKKEI 225 component stocks or a NIKKEI 225 index ETF	Change positions between long and short on the NIKKEI 225 up to once a day based on if the S&P 400 moved up (go long) or down (go short); if the S&P 400 change exceeded a threshold. If already in the correct position, then no change is made.
Others?	

A separate trading model spreadsheet (called “Leading Indicator Performance - SP400 NIKKEI 225”) was written to evaluate the returns that a trading system using this information could achieve. It was necessary to incorporate the exchange rate between Japanese Yen and US dollars, as the NIKKEI 225 is priced in Japanese Yen. Since the exchanges operate on different holiday calendars, the trading days of the components of S&P 400 and the NIKKEI 225 had to be aligned. The trading model is to look at the direction that the S&P 400 moves at the close of a day’s trading, and if it is up, keep or change to a long position on the NIKKEI 225 index; if the S&P 400 closed lower, then keep or change to a short position on the NIKKEI 225.

Figure 15 shows how well the S&P 400 direction predicted the NIKKEI 225 direction, as a function of how large the market move was.

At first the trading model showed great returns, over 3x a year over the same 5+ year period analyzed in the previous examples. Then it was realized that any change of position (long to short, or reverse) would be made at the following day’s opening price, not the previous day’s closing price on the NIKKEI 225, as the nature of any change needed would not be known until the middle of the night in Tokyo when the S&P 400 closed on Wall Street. The cross-correlation matrices of Figures 12 and 13 were made on a time-series of closing prices. However the market has time to move between its close and its next open, diminishing some of the gains that could be made if it opened right were it last closed.

To correct this, the valuation model was updated to be the following:

Previous Position	New Position	End of today value
Long	Long	$(\text{Yesterday's end of day value}) * (\text{Today's closing price}) / (\text{Yesterday's closing price})$
Short	Long	$(\text{Yesterday's end of day value}) * [(\text{Yesterday's closing price}) / (\text{Today's opening price})] * [1 - (\text{commission} + \text{spread})] * [(\text{Today's closing price}) / (\text{Today's opening price})]$
Long	Short	$(\text{Yesterday's end of day value}) * [(\text{Today's opening price}) / (\text{Yesterday's closing price})] * [1 - (\text{commission} + \text{spread})] * [(\text{Today's opening price}) / (\text{Today's closing price})]$
Short	Short	$(\text{Yesterday's end of day value}) * (\text{Yesterday's closing price}) / (\text{Today's closing price})$

With this, the returns dropped down to a little over 50% per year (after tuning), as seen in Figure 16. This figure shows that adjusting parameters such as the threshold on where to consider the prices in an input dataset to be “stable” instead of rising or falling, along with the buy/sell spread with commission, can tune the trading model to achieve higher returns. A slight threshold (1%) improved the trading return by 1/3 over no threshold.

It is infrequent that the S&P 400 opens at a price other than at which it closed on the previous trading day. In contrast, the NIKKEI 225 opening price is often displaced from the prior trading day’s closing price – I would gather reflecting adjustments to account for where the US and other major exchanges closed in the interim. Thus a good portion of the discrepancy in the NIKKEI 225 price at closing on one day to the S&P 400 leading indicator’s projection of where it will close the following day disappears before the Tokyo Stock Exchange reopens. This would explain the significantly lower returns projected versus a simpler trading model where we change positions at the previous day’s closing price instead of the following day’s opening price.

The trading return versus time is shown in Figure 17. It is interesting to see that the return is not constant over the study period. Instead, there was a region of very high returns (over 100%/year) between October of 2008 and October of 2009, with one gap in June of 2009, where returns were negative. Thus understanding when to use this method (corresponding to when returns are great) and when not (i.e. when returns are dismal) could greatly improve the overall performance.

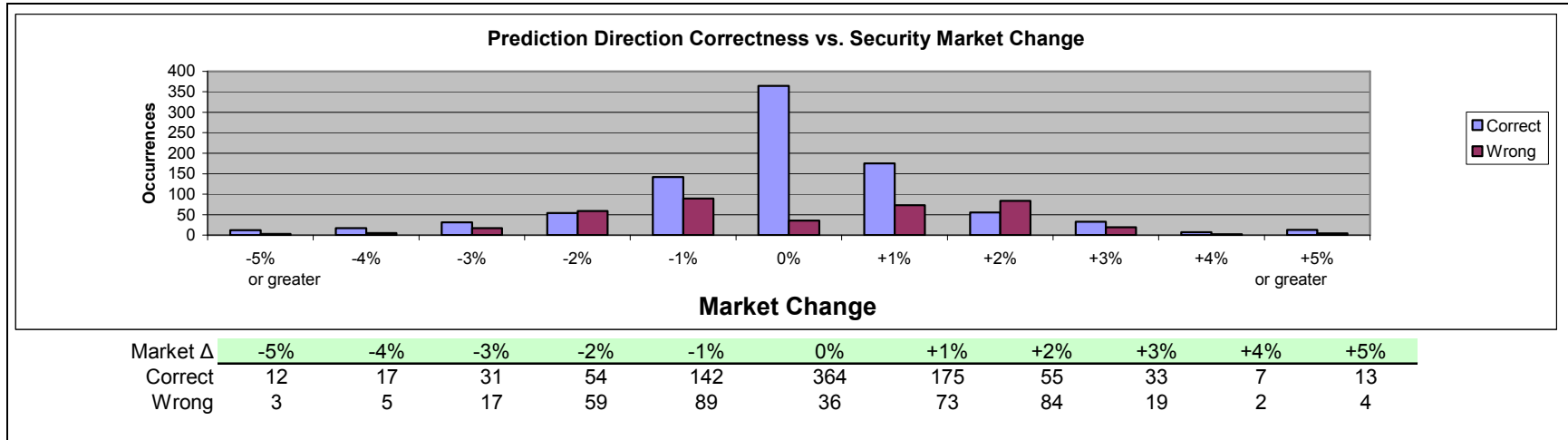


Figure 15

Trading **NIKKEI 225**
on indicator **S&P 400**

Up/Down Threshold (determines if indicator is "stable" or "trending")

		0%	0.50%	1%	1.50%	2%	2.50%	3%	3.50%	4%	4.50%	5%
Spread + Commission	0.25%	38.6%	47.4%	52.6%	42.3%	39.7%	48.7%	40.4%	17.8%	10.4%	18.6%	21.8%
	0.50%	4.9%	22.0%	34.4%	31.0%	32.5%	44.1%	36.8%	15.8%	8.8%	17.4%	20.8%
	1.0%	-40.0%	-16.6%	4.0%	10.9%	19.3%	35.3%	30.0%	12.0%	5.6%	14.9%	19.0%
	2.0%	-80.6%	-61.2%	-37.9%	-20.6%	-3.4%	19.2%	17.1%	4.7%	-0.5%	10.2%	15.4%

CAGR over 5.28 years

Figure 16

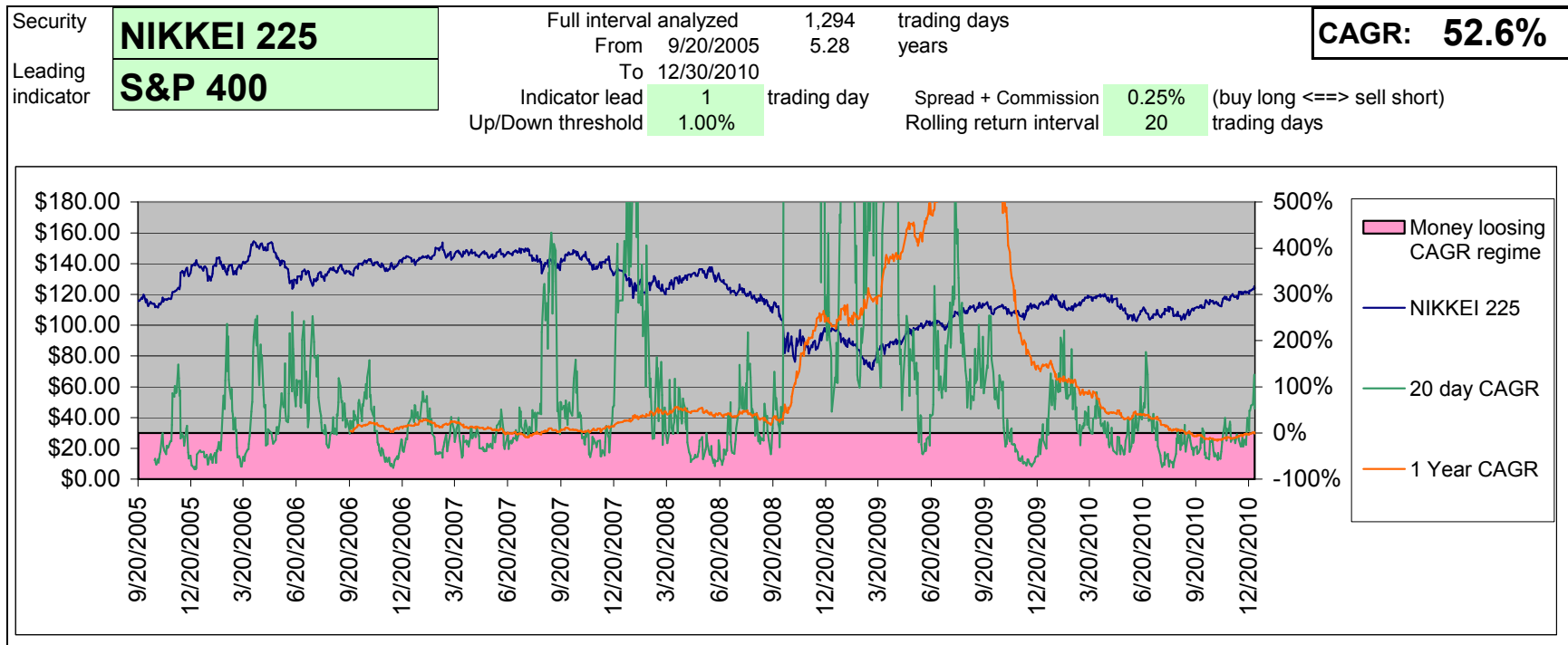


Figure 17: Trading returns using yesterday's S&P 400 price direction to set today's position in the NIKKEI 225

Conclusion

An Excel spreadsheet has been developed which will cross correlate all combinations of 20 time series. Two methods have been shown for displaying the 4 dimensional result of such cross correlation analysis. Feedback from readers is sought on which of these is more useful, or how to improve them, or suggestions for other approaches to pursue.

It was shown that the character of predictions can vary depending on how they were produced. Two of the types shown are next day, direction only; and weeks into the future, with full price curve prediction.

Two other Excel spreadsheets were developed to test the trading performance achievable from example leading indicators. When plausible trading models were driven by the two prediction types discussed, reasonable performance was seen on the day-ahead and dismal performance on the weeks-ahead projections.

Substantial variation was seen in the financial performance of the trading models over time. Understanding the conditions under which such trading models yield high performance and conversely where they perform badly should allow one to significantly improve overall financial returns by selectively using these trading models only when they generate high returns.