Momentum Investing Research Compendium

Published June 12, 2012

Exploiting Corporate Bond Responses to Aggregate Default Risk Shocks

May 25, 2012

How do general economic conditions and economy-wide default risk shocks affect corporate bond returns, especially past winners and losers? In the May 2012 draft of their paper entitled "Sources of Momentum in Bonds", Hwagyun Kim, Arvind Mahajan and Alex Petkevich investigate the relationship between U.S. corporate bond momentum portfolio returns and U.S. aggregate default risk. They measure the momentum effect as average monthly gross returns of overlapping hedge portfolios formed each month by buying (selling) the equally weighted tenth of bonds with the highest (lowest) total cumulative returns over the past six months and holding for six months, with a skip-month between ranking and holding intervals. They measure aggregate default risk as the prior-month yield spread between the Moody's CCC corporate bond index and the 10-year U.S. Treasury note. They define default risk shocks as deviations from the linear relationships between default risk this month and its values the prior two months. They define high (low) default risk shock conditions as those above (below) the inception-to-date median value of the series. Using price and yield data for all listed U.S. corporate bonds (excluding convertible bonds, asset-backed securities and bonds with very low capitalization) during January 1995 (101 bonds) through December 2010 (2,513 bonds), *they find that:*

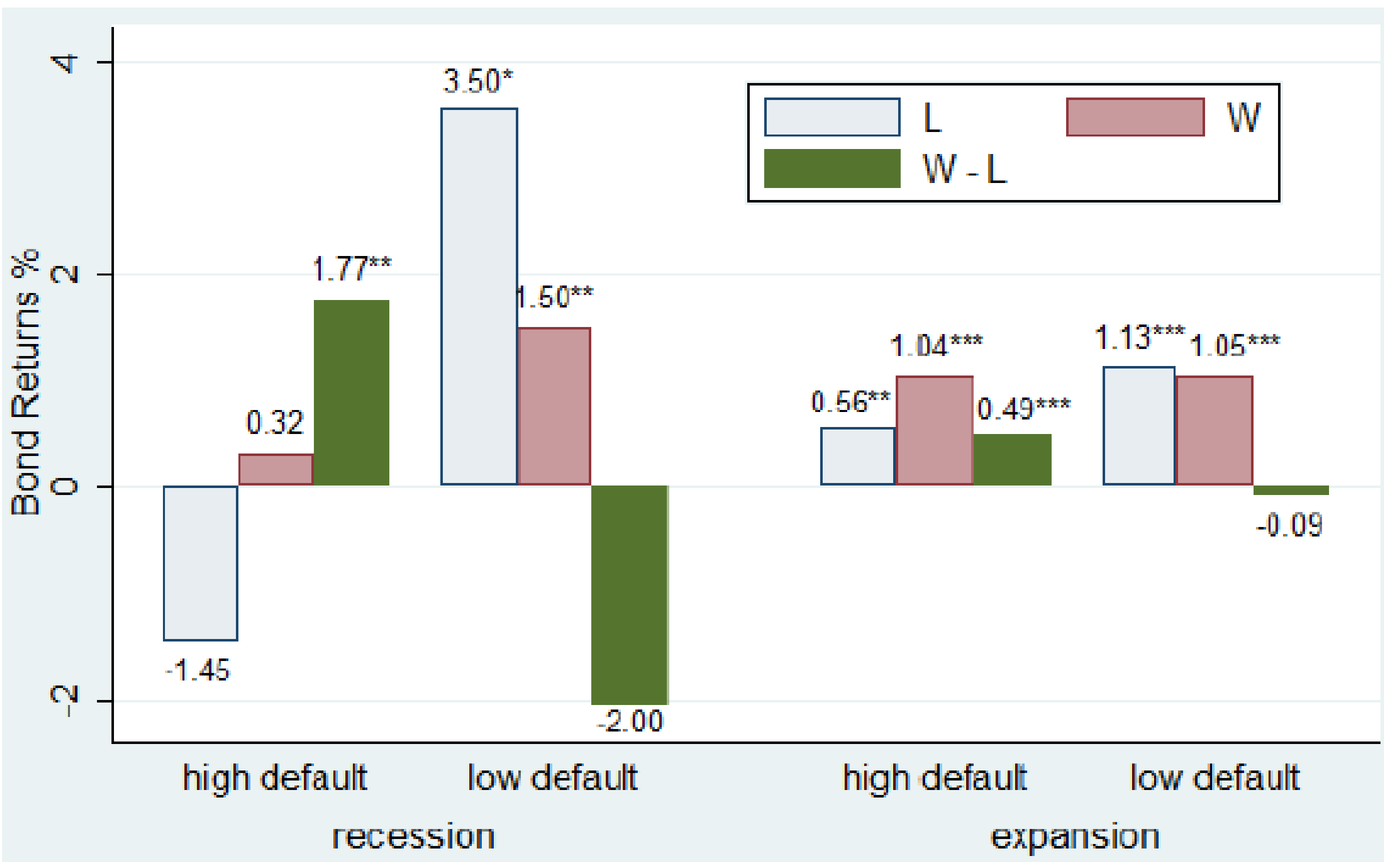
- Over the entire sample period, the gross momentum effect for U.S. corporate bonds is an insignificant 0.19% per month.
- However, the gross momentum effect is elevated (0.61% per month) during months after high default risk shocks and depressed (-0.26% per month) during months after low default risk shocks. Of 192 monthly observations, 100 (92) follow high (low) default risk shocks.
- Results are reasonably consistent for 1995-2002 and 2003-2010 subperiods, with gross momentum effects of 0.42% per month and 0.84% per month, respectively, during months after high default risk shocks.
- Over the National Bureau of Economic Research (NBER)-designated U.S. economic cycle (see the chart below):
  - The strongest gross momentum effect occurs during months after high default risk shocks when the economy is contracting (1.77% per month). [However, the effect derives largely from poor performance of losers, rendering a momentum strategy impractical for most investors.]
  - The gross momentum effect is also evident during months after high default risk shocks when the economy is expanding (0.49% per month), but the effect disappears during months after low default risk shocks for expansions.
- Excluding low-rated bonds eliminates the momentum effect, even during months after high default risk shocks.
- U.S. government bonds display no momentum effect, but it appears weakly during

months after high U.S. default risk shocks for bonds of other countries traded in the U.S. market.

The following chart, taken from the paper, summarizes the momentum effect for U.S. corporate bond portfolios during months after high and low default risk shocks, segmented by NBER contraction (recession) and expansion conditions during 1995 through 2010. The winner minus loser (W-L) returns measure the momentum effect. Superscripts *, ** and *** indicate progressively stronger statistical significance (which depends on return magnitudes, return variabilities and subsample sizes).

Results indicate that the bond momentum effect (W-L) is significant under both weak and strong economic conditions, but only during months after high default risk shocks.

Since shorting specific corporate bonds is problematic, the import for long-only bond investors is to avoid (focus on) corporate bonds during recessions after prior-month high (low) default risk shocks.



In summary, *evidence indicates that bond investors should avoid (exploit) U.S. corporate bonds during recessions after prior-month high (low) shocks to aggregate U.S. default risk.*

Cautions regarding findings include:

- As noted, most investors cannot short specific corporate bonds, undermining the practical import of the main themes of the study.

- Return calculations are gross, not net. Including reasonable trading frictions, which tend to be high for momentum strategies because of high turnover, would reduce reported returns and may affect findings. It is plausible that speculative grade bonds and months after large increases in aggregate default risk relate to relatively high trading frictions.
- The sample period is not long in terms of secular inflation trends.
- Statistical significance tests assume tame return distributions.

Originally published at http://www.cxoadvisory.com/20940/economic-indicators/exploiting-corporate-bond-responses-to-aggregate-default-risk-shocks/ on May 25, 2012.

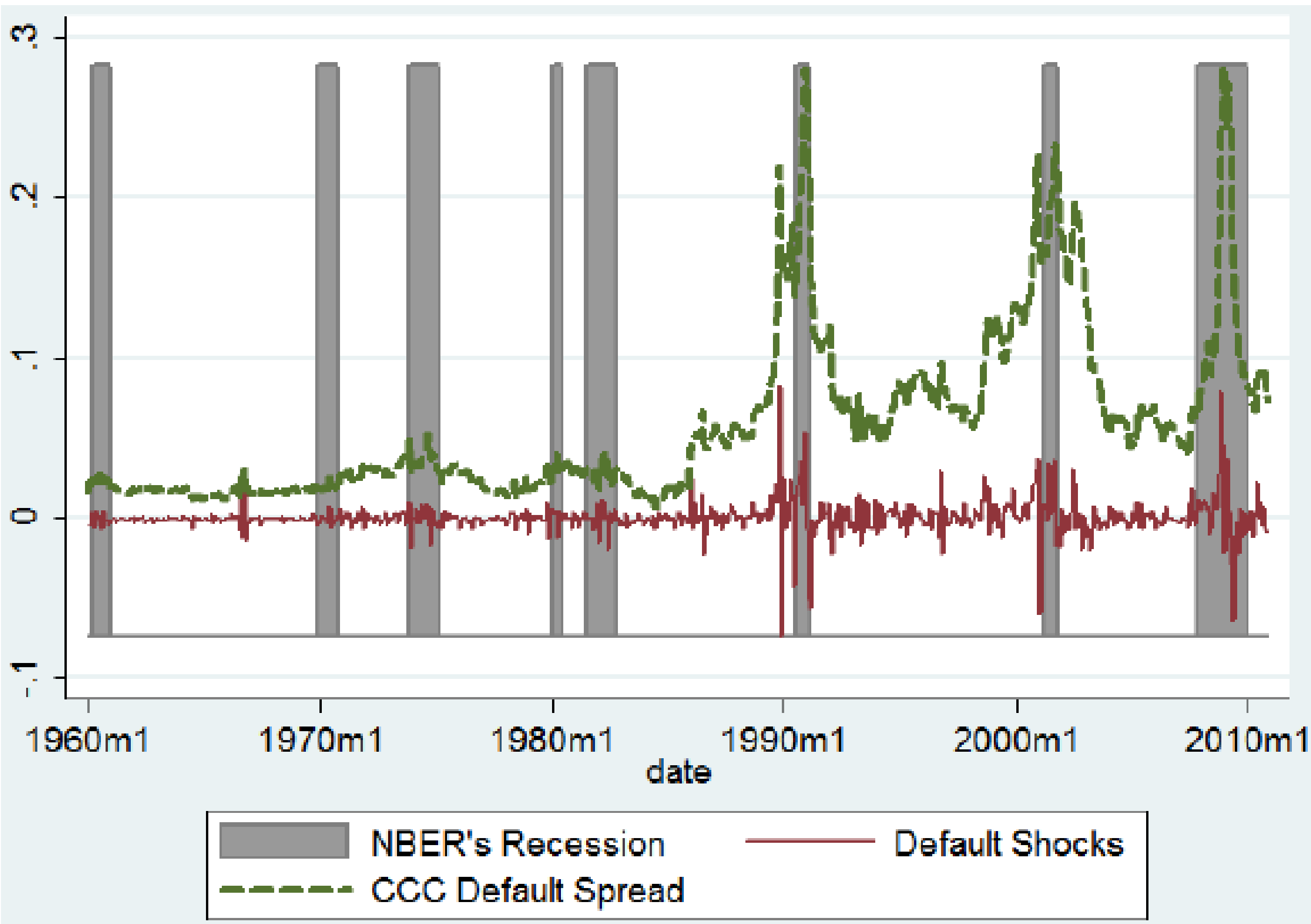
Stock Price Momentum and Aggregate Default Risk Shocks

May 25, 2012

Are there economic conditions that favor stock price momentum investing? In the May 2012 draft of their paper entitled "Momentum and Aggregate Default Risk", Arvind Mahajan, Alex Petkevich and Ralitsa Petkova investigate the relationship between stock momentum portfolio returns and U.S. aggregate default risk. They measure the momentum effect as average monthly gross returns of overlapping hedge portfolios formed each month by buying (selling) the equally weighted tenth of stocks with the highest (lowest) cumulative returns over the past six months and holding for six months, with a skip-month between ranking and holding intervals. They measure aggregate default risk as the prior-month yield spread between the Moody's CCC corporate bond index and the 10-year U.S. Treasury note. They define default risk shocks as deviations from the linear relationships between default risk this month and its values the prior two months. They define high (low) default risk shock conditions as those above (below) the inception-to-date median value of the series. Using monthly returns for a very broad sample of AMEX/NYSE/NASDAQ stocks during 1960 through 2009 and monthly default risk spreads since 1954, *they find that:*

- During 1960 through 2009, the average monthly gross return of the winner (loser) sides of momentum portfolios is 1.74% (0.95%), yielding a gross overall momentum effect of 0.79% per month.
- The gross momentum effect is elevated (1.93% per month) during months after high default risk shocks and depressed (-0.64% per month) during months after low default risk shocks.
- Over the National Bureau of Economic Research (NBER)-designated U.S. economic cycle:
  - During expansions, the overall gross momentum effect is 0.85% per month, 1.74% per month during months after high default risk shocks and essentially zero during months after low default risk shocks.
  - During contractions, the overall gross momentum effect is 0.18% per month, 2.76% per month during months after high default risk shocks and -3.75% during months after low default risk shocks.
- The momentum effect tends to decrease as firm investment grade increases.
- Findings generally hold after controlling for size, book-to-market and industrial production growth factors, and during pre-1960 and post-1995 subperiods when the overall momentum effect is weak.
- Findings extend to UK, German, French and Dutch equity markets based on respective monthly stock returns during 1985 through 2010 and contemporaneous U.S. default risk data. During months after high (low) U.S. default risk shocks, respective gross momentum effects are 2.29%, 1.00%, 1.57% and 2.09% (lower or absent).

The following chart, taken from the paper, plots U.S. default risk levels (yield spread between Moody's CCC corporate bond index and 10-year U.S. Treasury note) and shocks since 1960, with shaded intervals corresponding to NBER economic contractions. The correlation between default risk level and economic contractions is about 0.30, but that between default risk shocks and economic contractions is only about 0.05. In other words, default risk shocks define default conditions largely unrelated to general economic state (but, as indicated above, closely related to the stock price momentum effect). Volatility of default risk shocks suggests that modifying a momentum strategy with default risk shock signals may substantially increase portfolio turnover and associated trading frictions.



In summary, *evidence indicates that investors may be able to enhance returns from momentum investing in individual stocks by focusing on speculative grade stocks during months following increases in aggregate U.S. default risk.*

Cautions regarding findings include:

- Return calculations are gross, not net. Including reasonable trading frictions, which tend to be high for momentum strategies because of high turnover, would reduce reported returns and may affect findings. It is plausible that speculative grade stocks and months after large increases in aggregate default risk relate to relatively high trading frictions.
- Including costs of shorting for hedge portfolios would also reduce reported returns.

Shorting may not be feasible for all loser stocks.
- Statistical significance tests assume tame return distributions. Also, there are so many studies on the momentum effect in U.S. stocks over the sample period that aggregate data snooping bias in the research stream is plausible.

Originally published at http://www.cxoadvisory.com/20935/economic-indicators/stock-price-momentum-and-aggregate-default-risk-shocks/ on May 25, 2012.

Mutual Fund Alpha Momentum

May 21, 2012

Does momentum investing work when implemented via mutual fund alpha? In his February 2012 paper entitled "Short Term Alpha as a Predictor of Future Mutual Fund Performance" (the National Association of Active Investment Managers' 2012 Wagner Award runner-up), Michael Hartmann examines a momentum-based approach for selecting outperforming equity mutual funds by investment style. He considers nine equity investment styles: Large Capitalization Growth, Large Capitalization Blend, Large Capitalization Value, Mid Capitalization Growth, Mid Capitalization Blend, Mid Capitalization Value, Small Capitalization Growth, Small Capitalization Blend and Small Capitalization Value. He measures momentum based on fund alpha calculated by linear regression of returns versus those of the S&P 500 Index over the past 20, 40, 60, 80 and 100 calendar days. He then forms non-overlapping portfolios of the three highest-alpha funds (weighted equally) for each style every 45, 70, 95, 120, 135 and 170 calendar days over the entire sample period and compares compound annual return rates for these portfolio series to those for corresponding Russell total return style indexes. Using daily total returns for open-ended mutual funds currently available via the no-transaction mutual fund platform at Charles Schwab & Co. and daily returns for the S&P 500 Index from the end of June 1999 through December 2011, along with sample period compound rates of return for Russell benchmark indexes, *he finds that:*

- Across 225 possible combinations of equity investment style, alpha calculation interval and portfolio holding interval, the alpha winner portfolios outperform respective benchmark indexes by an average annual compound margin of 3.19%, with 193 of 225 (86%) beating their benchmark.
- The combinations with the highest average annual compound rate of return are those with alpha calculation intervals of 60 and 80 days, and holding intervals of 95 to 145 days (see the first table below).
- Outperformance varies considerably across investment styles, with Small Capitalization Blend and Small Capitalization Value exhibiting greatest outperformance (see the second table below).

The following table, taken from the paper, summarizes alpha momentum portfolio compound annual returns over the entire sample period by alpha calculation interval and holding interval. Results suggest an optimal alpha calculation interval of 60-80 days and an optimal holding interval of 95-145 days.

Irregular variations across combinations indicate a material amount of luck in results.

Alpha Calculation Look back Period (Days)	Selected Investment Holding Period (Days) 45	70	95	120	145	170	Average Return Look back Period
20	5.87%	5.11%	6.62%	5.97%	5.10%	5.15%	5.64%
40	5.29%	6.17%	6.99%	6.90%	8.46%	6.07%	6.65%
60	8.00%	7.51%	6.99%	8.28%	8.20%	3.98%	7.16%
80	7.00%	7.79%	8.41%	7.55%	6.88%	8.13%	7.63%
100	6.50%	7.04%	7.35%	6.84%	6.99%	5.97%	6.84%
Average Return for Holding Period	6.53%	6.72%	7.27%	7.11%	7.13%	5.86%	

The next table, also from the paper, summarizes alpha momentum portfolio compound annual outperformance relative to corresponding Russell indexes over the entire sample period by equity investment style. Again, irregularities suggest a large role for luck in results.

	Value	Blend	Growth	Average Annual Rate of Return for Capitalization Size
Large Cap	3.77%	4.43%	2.14%	3.45%
Mid Cap	0.36%	0.43%	3.14%	1.31%
Small Cap	2.99%	5.23%	5.91%	4.71%
Average Annual Rate of Return for Investment Style	2.37%	3.36%	3.73%	

In summary, *evidence indicates that investors may be able to exploit persistence of market outperformance measured over the past few months among U.S. equity mutual funds.*

Cautions regarding findings include:

- The high-level summary statistics in the paper do not match the described methodology. Five alpha measurement intervals times six holding intervals time nine investment styles generates 270 combinations. The tables on pages 17-25 of the study indicate that 238 of these 270 combinations (88%) outperform their Russell style index benchmarks. The average annual compound rate of return outperformance of 3.19% across all combinations may not apply to this total set. The author acknowledges the mismatch between summary and raw results and intends to update the paper and ask NAAIM to replace the current version.

- The data collection and processing burden of the momentum calculation method in the study is substantial, and potentially costly if delegated. The simpler and widely used approach of ranking funds based on cumulative lagged returns may be effective.
- Examination of a large number of combinations incorporates data snooping bias such that the performance of the best (worst) combinations likely overstates (understates) expected future performance.
- Extending the methodology to funds for non-equity asset classes would involve regression against some index other than the S&P 500 Index.
- Mutual fund trading restrictions (fees for short holding periods) may interfere with strategy execution for short holding intervals.

Originally published at http://www.cxoadvisory.com/20905/mutual-hedge-funds/mutual-fund-alpha-momentum/ on May 21, 2012.

Combining Sector and Asset Class ETF Momentum

May 18, 2012

A subscriber asked: "Have you looked at combining sector and asset class momentum models? This strategy would add alternative asset classes plus cash to the nine sectors." A combined strategy encompasses nine sector exchange-traded funds (ETF) defined by the Select Sector Standard & Poor's Depository Receipts (SPDR) per "Simple Sector ETF Momentum Strategy" plus the eight ETFs and cash that cut across asset classes per "Simple Asset Class ETF Momentum Strategy", as follows:

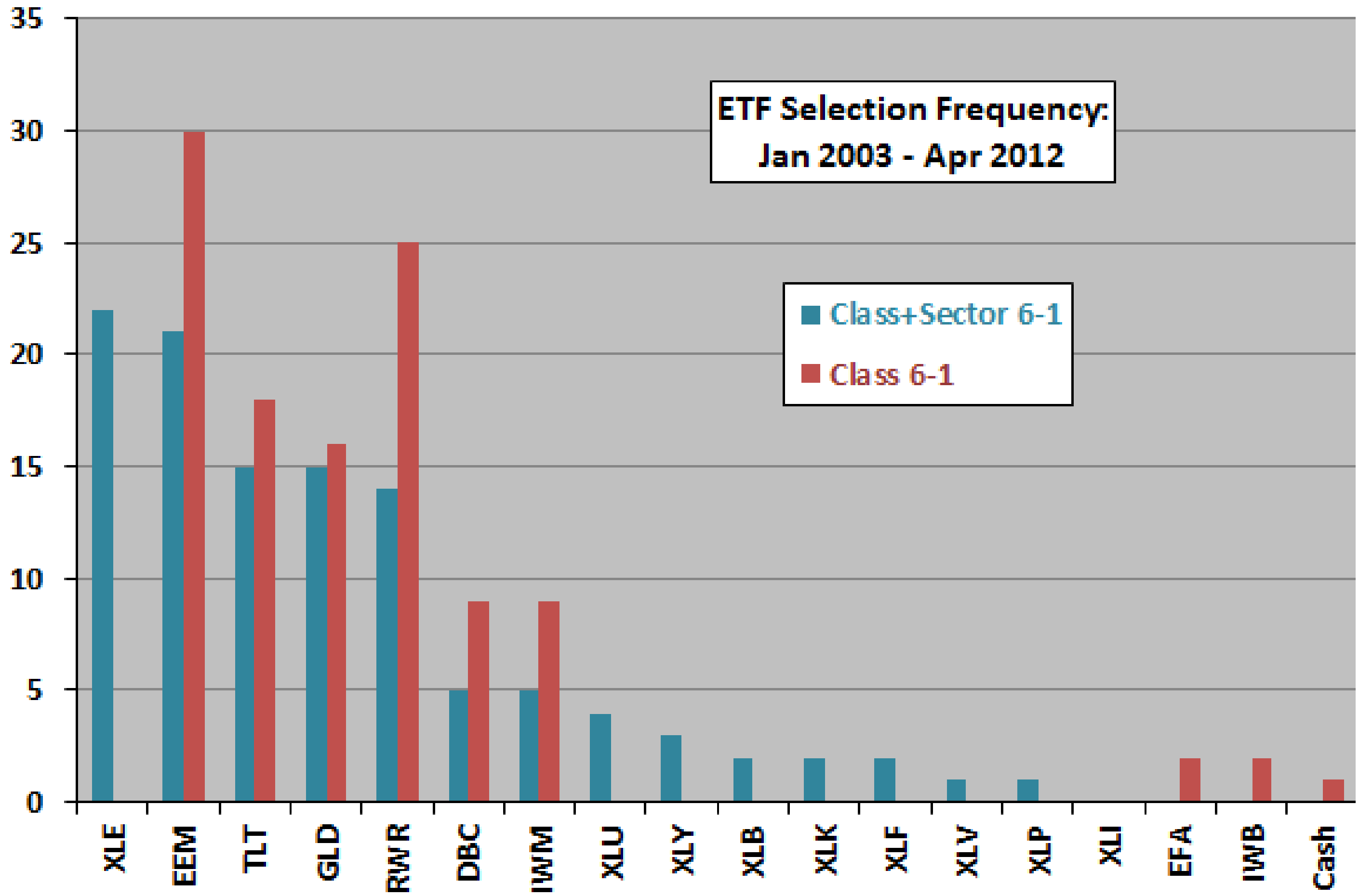
Materials Select Sector SPDR (XLB)
Energy Select Sector SPDR (XLE)
Financial Select Sector SPDR (XLF)
Industrial Select Sector SPDR (XLI)
Technology Select Sector SPDR (XLK)
Consumer Staples Select Sector SPDR (XLP)
Utilities Select Sector SPDR (XLU)
Health Care Select Sector SPDR (XLV)
Consumer Discretionary Select SPDR (XLY)

PowerShares DB Commodity Index Tracking (DBC)
iShares MSCI Emerging Markets Index (EEM)
iShares MSCI EAFE Index (EFA)
SPDR Gold Shares (GLD)
iShares Russell 1000 Index (IWB)
iShares Russell 2000 Index (IWM)
SPDR Dow Jones REIT (RWR)
iShares Barclays 20+ Year Treasury Bond (TLT)
3-month Treasury bills (Cash)

We consider a simple (6-1) strategy that allocates all funds each month to the one sector or asset class ETF/cash with the highest total return over the past six months (effectively pitting the sector winner against the asset class winner). Using monthly dividend-adjusted closing prices for the ETFs over the period July 2002 (limited by data availability for enough asset class ETFs) through April 2012 (118 months), *we find that:*

The following chart compares the distribution of winning ETFs based on past six-month momentum over the available sample period for the combined sector and asset class strategy (Class+Sector 6-1) and the asset class strategy alone (Class 6-1). Availability of sector ETFs substantially displaces equity, real estate and commodities ETFs.

How does applying the Class+Sector 6-1 strategy translate into cumulative returns?

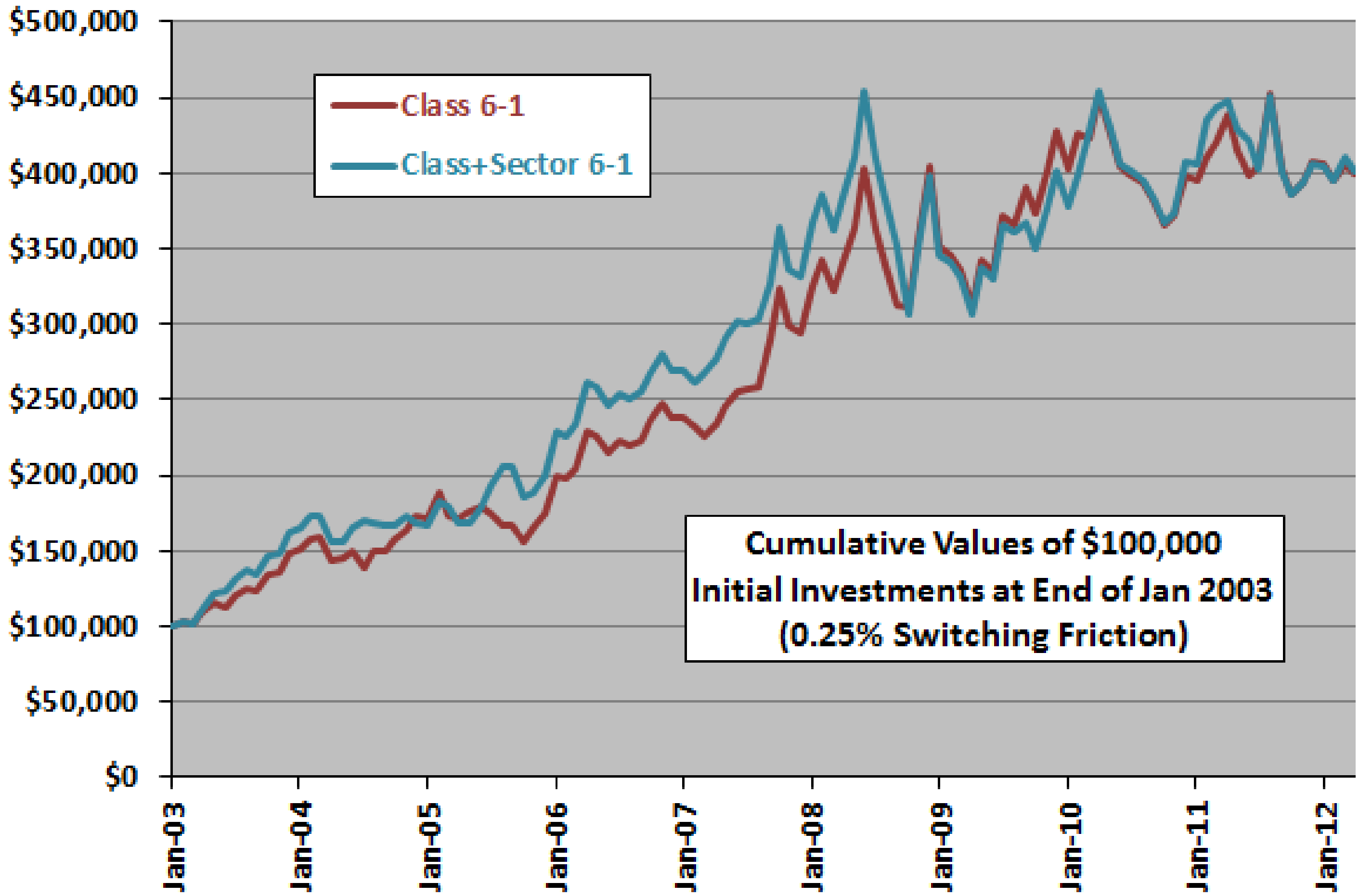


The next chart compares the cumulative values of $100,000 initial investments in the Class 6-1 and the Class+Sector 6-1 momentum strategies over the available sample period. Calculations derive from the following assumptions:

- Reallocate at the close on the last trading day of each month (assume that total six-month past returns for the ETFs can be calculated just before the close).
- Trading (switching) friction is 0.25% of the balance whenever there is an ETF switch.
- Ignore any tax implications of trading.

At the assumed level of switching friction, the two strategies perform similarly, with a slight edge to the combined strategy. The number of switches for Class+Sector 6-1 is 53, compared to 45 for Class 6-1, so a lower level of trading friction would favor the combined strategy.

The average net monthly return for Class+Sector 6-1 (Class 6-1) is 1.44% (1.43%), with standard deviation 6.04% (5.92%), confirming performance similarly.



In summary, *evidence from simple tests indicates that a combined asset class and U.S. equity sector momentum ETF strategy performs similarly to the asset class momentum ETF strategy.*

The sector ETFs effectively displace large capitalization stock ETFs.

Cautions regarding findings include:

- Sample size is modest (about 20 independent six-month momentum ranking intervals).
- The selected ETF ranking interval derives from prior academic studies that most often use six-month and 12-month ranking intervals, with one-month holding intervals. This prior research may impound (and therefore transmit) data snooping bias, which is especially pernicious for small samples. Ranking intervals other than six months and holding periods other than one month may produce different results. For the above tests, using longer ranking and holding intervals would effectively reduce the already-small sample size. Optimizing the ranking and holding intervals would elevate data snooping bias.
- Potential wildness in ETF monthly return distributions limits confidence in results.

Originally published at http://www.cxoadvisory.com/20885/momentum-investing/combining-sector-and-asset-class-etf-momentum/ on May 18, 2012.

Combining Sector and Style ETF Momentum

May 18, 2012

A subscriber commented and asked: "You compare style ETF momentum to sector ETF momentum in 'Doing Momentum with Style (ETFs)'. Can you mix style and sector ETFs to form a combined momentum strategy and compare it with the individual style and sector momentum strategies?" A combined strategy encompasses the nine sector exchange-traded funds (ETF) defined by the Select Sector Standard & Poor's Depository Receipts (SPDR) plus the six ETFs that cut across market capitalization (large, medium and small) and value versus growth:

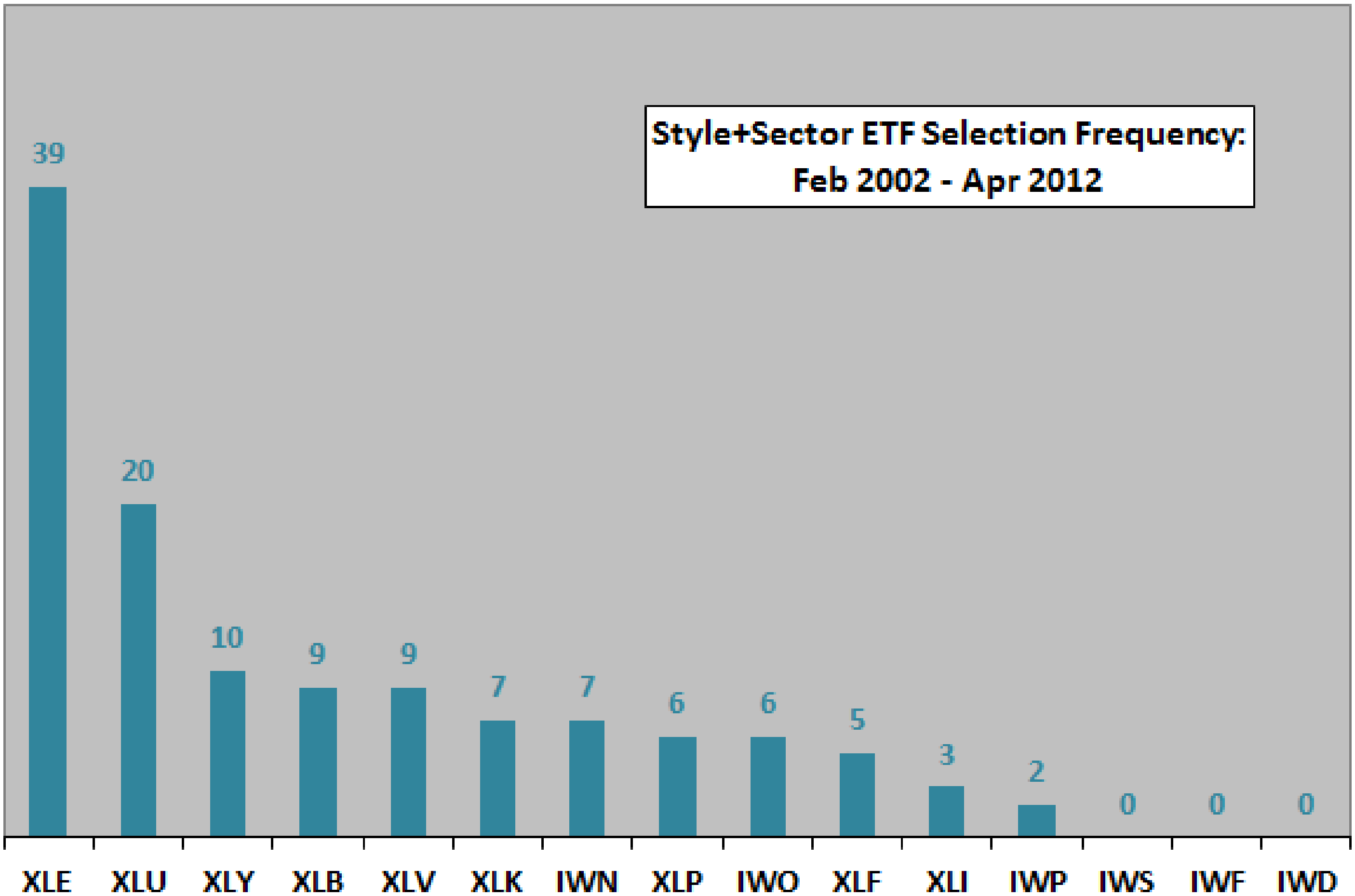
Materials Select Sector SPDR (XLB)
Energy Select Sector SPDR (XLE)
Financial Select Sector SPDR (XLF)
Industrial Select Sector SPDR (XLI)
Technology Select Sector SPDR (XLK)
Consumer Staples Select Sector SPDR (XLP)
Utilities Select Sector SPDR (XLU)
Health Care Select Sector SPDR (XLV)
Consumer Discretionary Select SPDR (XLY)

iShares Russell 1000 Value Index (IWD) – large capitalization value stocks.
iShares Russell 1000 Growth Index (IWF) – large capitalization growth stocks.
iShares Russell Midcap Value Index (IWS) – mid-capitalization value stocks.
iShares Russell Midcap Growth Index (IWP) – mid-capitalization growth stocks.
iShares Russell 2000 Value Index (IWN) – small capitalization value stocks.
iShares Russell 2000 Growth Index (IWO) – small capitalization growth stocks.

We consider a simple (6-1) strategy that allocates all funds each month to the one sector or style ETF with the highest total return over the past six months (effectively pitting the sector winner against the style winner). Using monthly dividend-adjusted closing prices for these 15 ETFs over the period August 2001 (limited by data availability for IWS/IWP) through April 2012 (129 months), *we find that:*

The following chart presents the distribution of winning ETFs based on past six-month momentum over the available sample period. The XLE energy sector ETF comprises 39 of the 123 monthly winners (32%). Style ETFs win only 15 months, and large capitalization stocks never win. The returns of all these U.S. equity ETFs are highly correlated. The sector ETFs are more finely segmented than the style ETFs, so they are generally more volatile and therefore more likely to win on momentum.

How does applying the 6-1 combined style and sector ETF momentum strategy translate into cumulative returns?



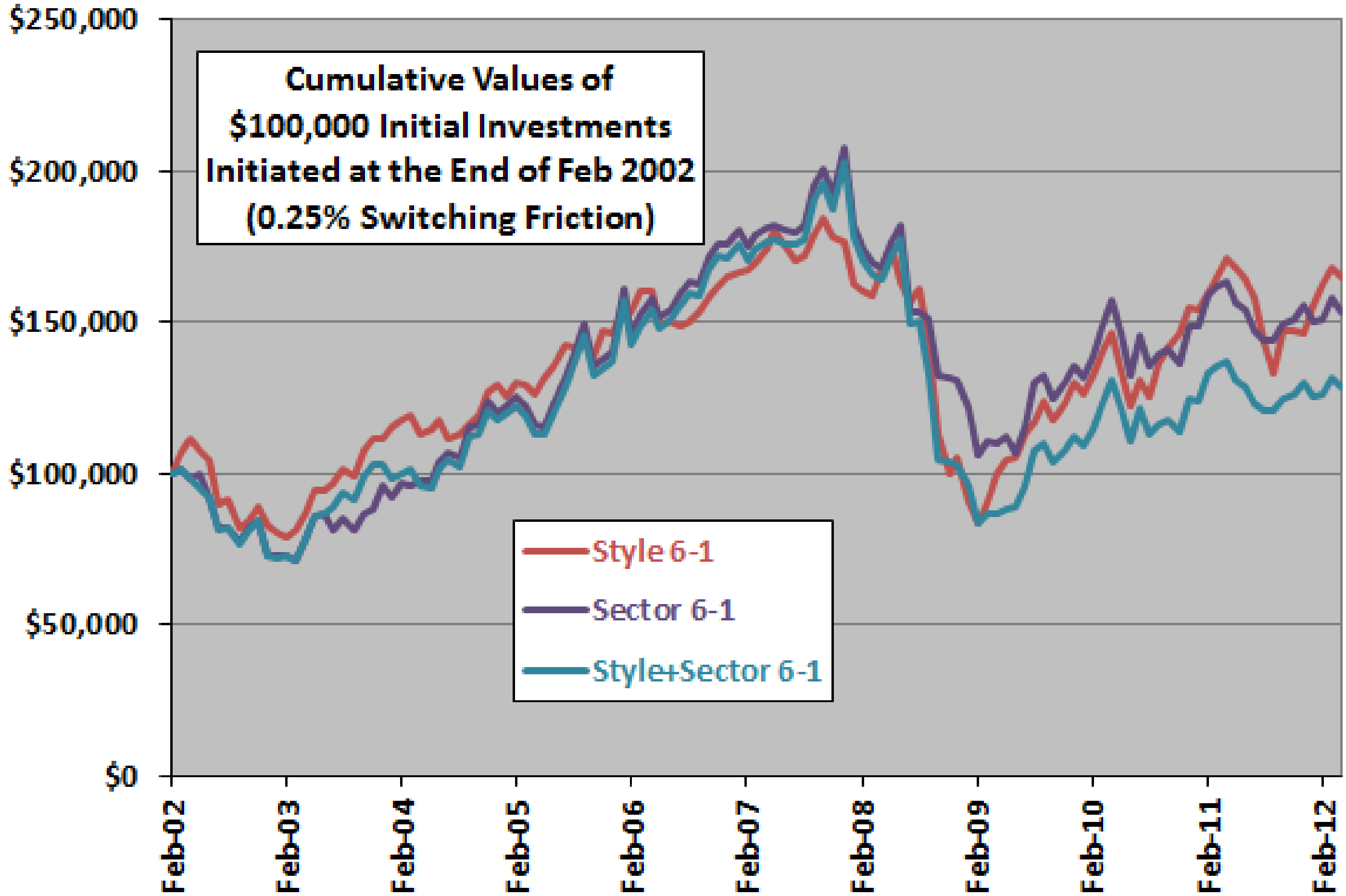
The next chart compares the cumulative values of $100,000 initial investments in each of the sector ETF, style ETF and combined 6-1 momentum strategies over the available sample period. Calculations derive from the following assumptions:

- Reallocate at the close on the last trading day of each month (assume that total six-month past returns for the ETFs can be calculated just before the close).
- Trading (switching) friction is 0.25% of the balance whenever there is an ETF switch.
- Ignore any tax implications of trading.

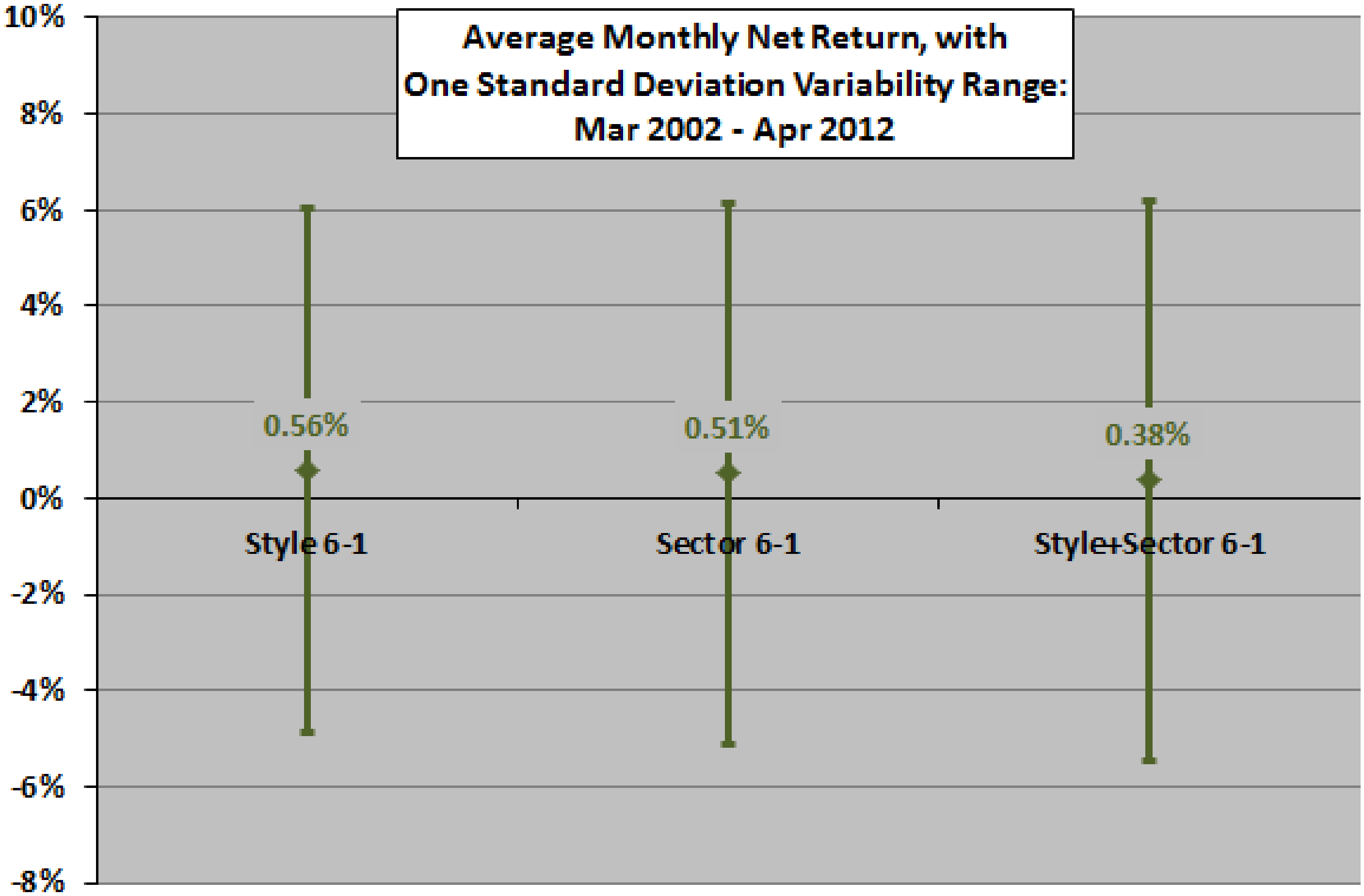
At the assumed level of switching friction, the net style ETF momentum strategy (Style 6-1) and net sector ETF momentum strategy (Sector 6-1, from "Simple Sector ETF Momentum Strategy") perform similarly. The combined strategy (Style+Sector 6-1) underperforms due to a few unlucky switches during the 2008-2009 market crash and elevated trading frictions.

The number of switches for the combined strategy is 53, compared to 38 for Style 6-1 and 49 for Sector 6-1.

How do average monthly returns, as alternative measures of strategy performance, compare?



The final chart depicts the average monthly net returns (with 0.25% switching frictions) and the standard deviations of monthly returns for the three sector ETF momentum strategies. As indicated by the above cumulative performance, Style 6-1 and Sector 6-1 have similar statistics, with the combined strategy lagging.



In summary, *evidence from simple tests indicates that a combined U.S. equity style and sector ETF momentum strategy underperforms the separate style and sector ETF momentum strategies due to a few unlucky switches and elevated trading friction.*

In other words, more choices are not always better for a momentum strategy.

Cautions regarding findings include:

- Sample size is modest (about 22 independent six-month momentum ranking intervals).
- The selected ETF ranking interval derives from prior academic studies that most often use six-month and 12-month ranking intervals, with one-month holding intervals. This prior research may impound (and therefore transmit) data snooping bias, which is especially pernicious for small samples. Ranking intervals other than six months and holding periods other than one month may produce different results. For the above tests, using longer ranking and holding intervals would effectively reduce the already-small sample size. Optimizing the ranking and holding intervals would elevate data snooping bias.
- Including ETFs representing other asset classes (such as bonds, commodities and international stocks) may enhance results, but may also increase number of position switches and therefore cumulative trading friction.
- Potential wildness in ETF monthly return distributions limits confidence in results.

Originally published at http://www.cxoadvisory.com/15011/momentum-investing/combining-sector-and-style-etf-momentum/ on May 18, 2012.

Alternative Asset Class ETF Momentum Allocations

May 9, 2012

A subscriber suggested an alternative to the "Simple Asset Class ETF Momentum Strategy" that weights asset class ETFs according to six-month lagged return ranking (such as 35-25-20-10-4-3-2-1) rather than allocating all funds to the winner. Do the diversification benefits of this alternative outweigh the loss of momentum purity? To investigate, we return to the following eight asset class exchange-traded funds (ETF), plus cash:

PowerShares DB Commodity Index Tracking (DBC)
iShares MSCI Emerging Markets Index (EEM)
iShares MSCI EAFE Index (EFA)
SPDR Gold Shares (GLD)
iShares Russell 1000 Index (IWB)
iShares Russell 2000 Index (IWM)
SPDR Dow Jones REIT (RWR)
iShares Barclays 20+ Year Treasury Bond (TLT)
3-month Treasury bills (Cash)

As one benchmark, we allocate all funds at the end of each month to the asset class ETF or cash with the highest total return over the past six months (6-1). As another benchmark, we maintain an equal-weighted (EW), monthly rebalanced portfolio of all nine asset classes. As alternatives, we test two momentum rank-weighted (RW), linearly-scaled combinations of all nine classes, one steep across ranks and one shallow. We also test EW combinations of the Top 5, Top 4, Top 3 and Top 2 momentum ranks. Using monthly adjusted closing prices for the asset class proxies and the yield for Cash over the period February 2006 (the earliest all ETFs are available) through April 2012 (75 months), *we find that:*

The following chart compares the gross cumulative values of $100,000 initial investments in the 6-1 and EW benchmarks and the steep and shallow RW alternatives. Calculations derive from the following assumptions:

- Reallocate/rebalance at the close on the last trading day of each month (assume that total six-month past returns for the ETFs can be calculated just before the close).
- Assume no trading frictions and no tax implications of trading (discussion below).

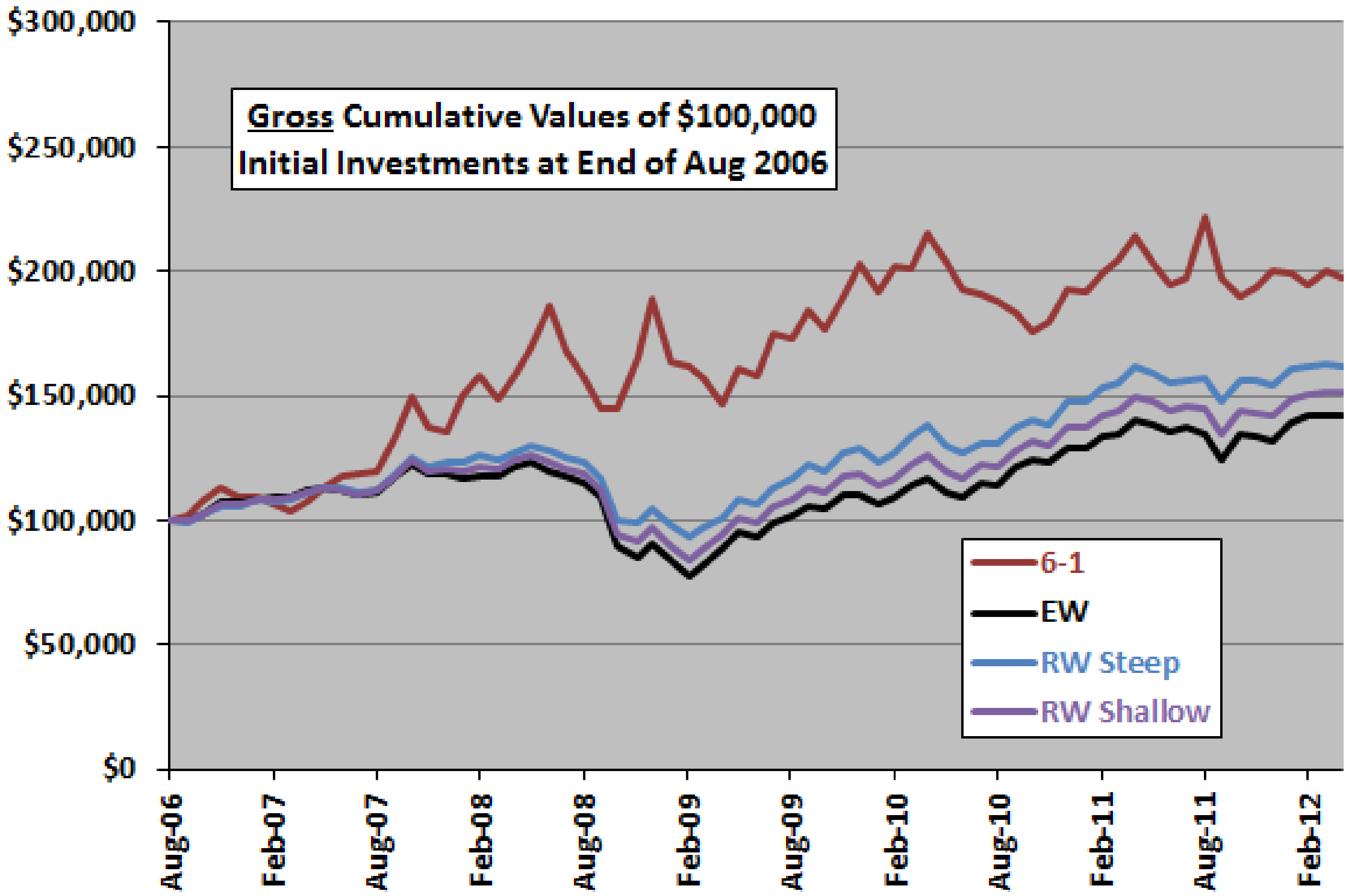
Gross average monthly returns and standard deviations of monthly returns are:

- 6-1: 1.20% and 6.30%, with risk-return ratio 0.19.
- EW: 0.61% and 4.32%, with risk-return ratio 0.14.

- RW Steep: 0.79% and 3.86%, with risk-return ratio 0.20.
- RW Shallow: 0.69% and 4.05%, with risk-return ratio 0.17.

Results suggest that portfolios employing momentum rank weighting across all asset class ETFs enhance simple EW diversification, but they do not beat pure momentum. Note that monthly trading frictions for the EW and RW strategies would be materially higher than that for the 6-1 strategy, such that the performance gap with the latter would widen for net performances.

What about just diversifying across a few of the top momentum-ranked asset class ETFs?



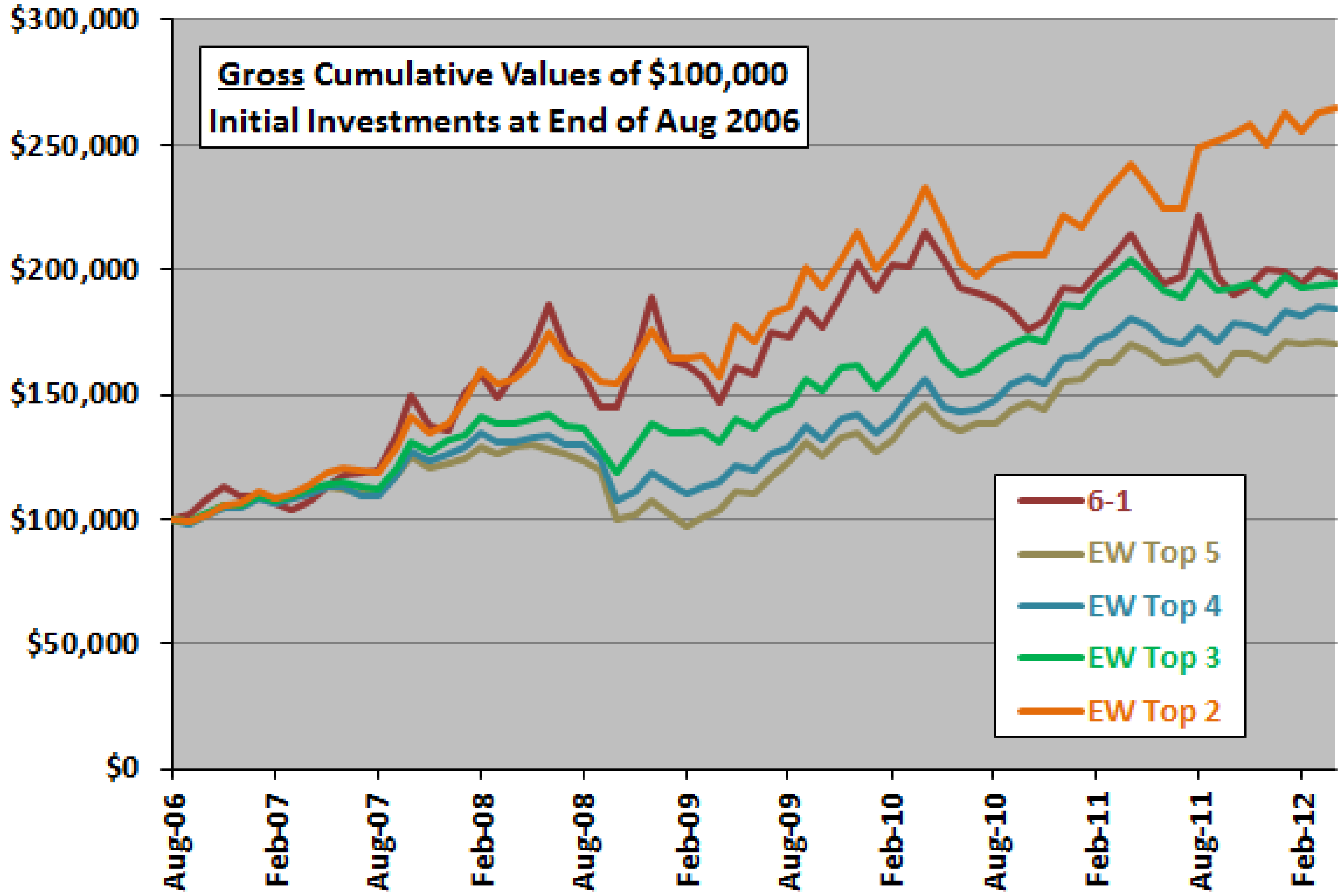
The next chart compares the gross cumulative values of $100,000 initial investments in the 6-1 strategy and alternatives EW combinations of the Top 5, Top 4, Top 3 and Top 2 momentum ranks.

Gross average monthly returns and standard deviations of monthly returns are:

- 6-1: 1.20% and 6.30%, with risk-return ratio 0.19.
- EW Top 5: 0.86% and 3.92%, with risk-return ratio 0.22.
- EW Top 4: 0.98% and 3.88%, with risk-return ratio 0.25.
- EW Top 3: 1.06% and 3.92%, with risk-return ratio 0.27.
- EW Top 2: 1.55% and 4.67%, with risk-return ratio 0.33.

Results generally suggest a classic trade-off between return and volatility, but lack of systematic progression indicates a material role of randomness. The outperformance of the EW Top 2 strategy relative to the 6-1 strategy may be due to randomness (see the first chart in "Simple Asset Class ETF Momentum Strategy Robustness/Sensitivity Tests", which indicates anomalously strong performance for the second momentum rank).

Note that monthly trading frictions for the four EW strategies would be progressively higher than that for the 6-1 strategy as the number of ETFs in the portfolio increases, enhancing the relative performance of the 6-1 strategy on a net basis.



In summary, *evidence from simple tests over a limited sample period of strategies that combine momentum and diversification: (1) support belief that these strategies attractively reduce return volatility; but, (2) mostly do not support belief that they beat pure momentum.*

Cautions regarding findings include:

- Sample size is very small (just 12 independent six-month momentum ranking intervals).
- As noted, ignoring trading frictions gives an advantage to EW and RW strategies over 6-1, because the fixed transaction costs would represent larger percentages of the smaller portfolio positions. Exact impact would depend on specific broker fees and portfolio size.
- Potential wildness in ETF monthly return distributions limits confidence in results.

Originally published at http://www.cxoadvisory.com/20199/momentum-investing/alternative-asset-class-etf-momentum-allocations/ on May 9, 2012.

Simple Asset Class ETF Momentum Strategy Robustness/Sensitivity Tests

May 9, 2012

How sensitive is the performance of the "Simple Asset Class ETF Momentum Strategy" to selecting ranks other than winners and to choosing a momentum ranking interval other than six months? This strategy each month ranks the following eight asset class exchange-traded funds (ETF), plus cash, on past return and rotates to the strongest class:

PowerShares DB Commodity Index Tracking (DBC)
iShares MSCI Emerging Markets Index (EEM)
iShares MSCI EAFE Index (EFA)
SPDR Gold Shares (GLD)
iShares Russell 1000 Index (IWB)
iShares Russell 2000 Index (IWM)
SPDR Dow Jones REIT (RWR)
iShares Barclays 20+ Year Treasury Bond (TLT)
3-month Treasury bills (Cash)

Available data are so limited that sensitivity test results may mislead. With that reservation, we perform two robustness/sensitivity tests: (1) comparison of returns for all nine ranks of winner through loser based on a ranking interval of six months and a holding interval of one month (6-1); and, (2) comparison of winner returns for ranking intervals ranging from one to 12 months (1-1 through 12-1) and for a six-month lagged six-month ranking interval (12:7-1) per "Isolating the Decisive Momentum (Echo?)", all with one-month holding intervals. Using monthly adjusted closing prices for the asset class proxies and the yield for Cash over the period July 2002 (or inception if not available then) through April 2012 (118 months), *we find that:*

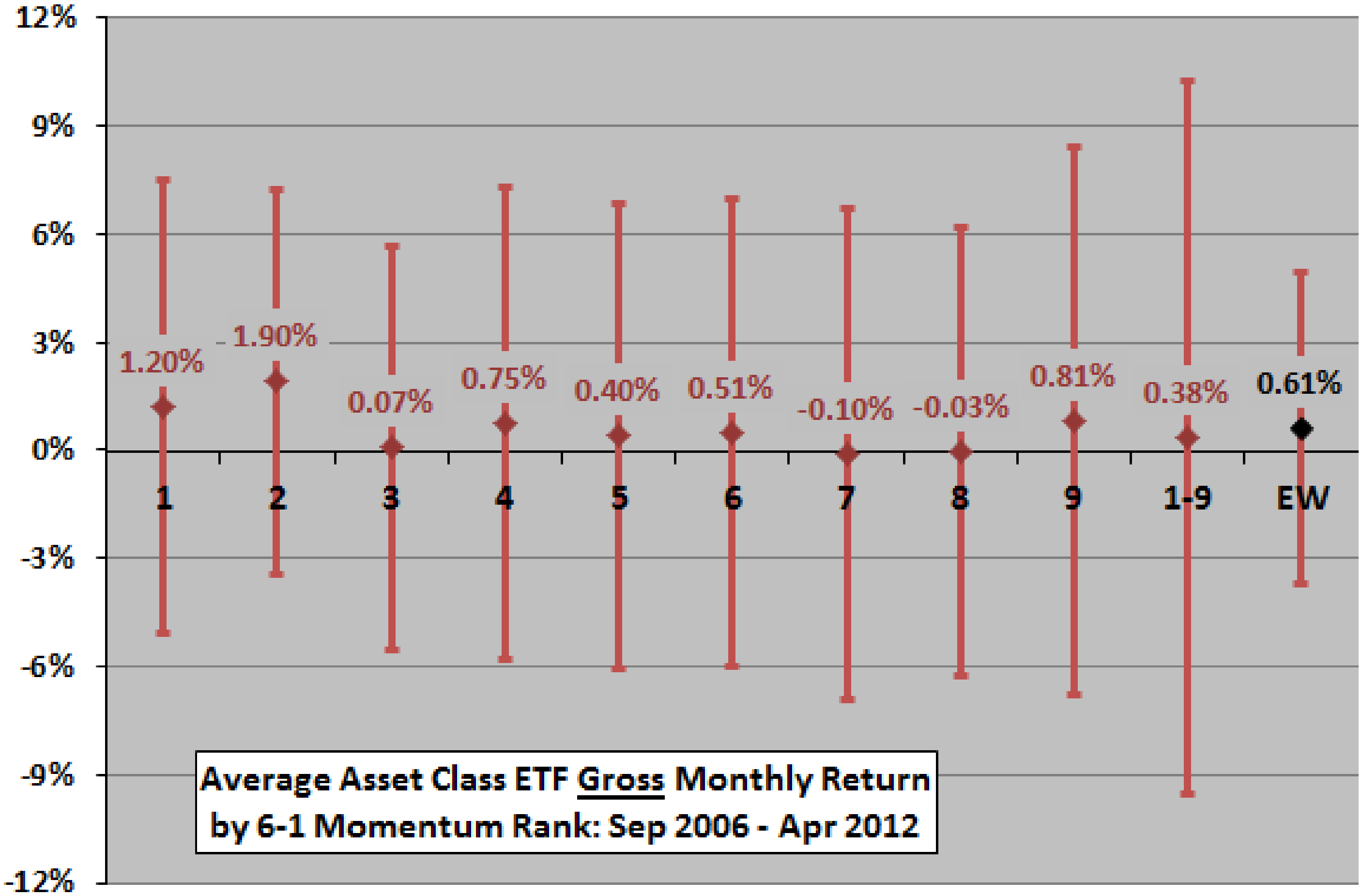
All calculations assume that monthly reallocation/rebalancing occurs at the close on the last trading day of each month (assuming that past returns for the ETFs can be calculated for ranking purposes just before the close).

The following chart shows average monthly 6-1 asset class momentum strategy gross returns for rank 1 (highest momentum) through rank 9 (lowest momentum) since September 2006, with one standard deviation variability ranges. September 2006 is the first month for which returns for all nine asset classes are available, rendering the sample period extremely short for confident inference. The chart also shows comparable statistics for an equally weighted, monthly rebalanced (EW) portfolio of the nine classes as a simple benchmark representing the value of diversification. Notable points are:

- Ranks 1 and 2 have the highest average returns, and the difference in average returns between ranks 1 and 9 is positive.
- Average returns do not decline systematically from rank 1 through rank 9. Rank 3 has the third lowest average return, and rank 9 has the third highest.

Results do not compelling support belief in asset class momentum strategy reliability. The extremely short sample period amplifies concern that the best ranking intervals may be lucky rather than fundamentally meaningful.

What happens for ranking intervals other than six months?



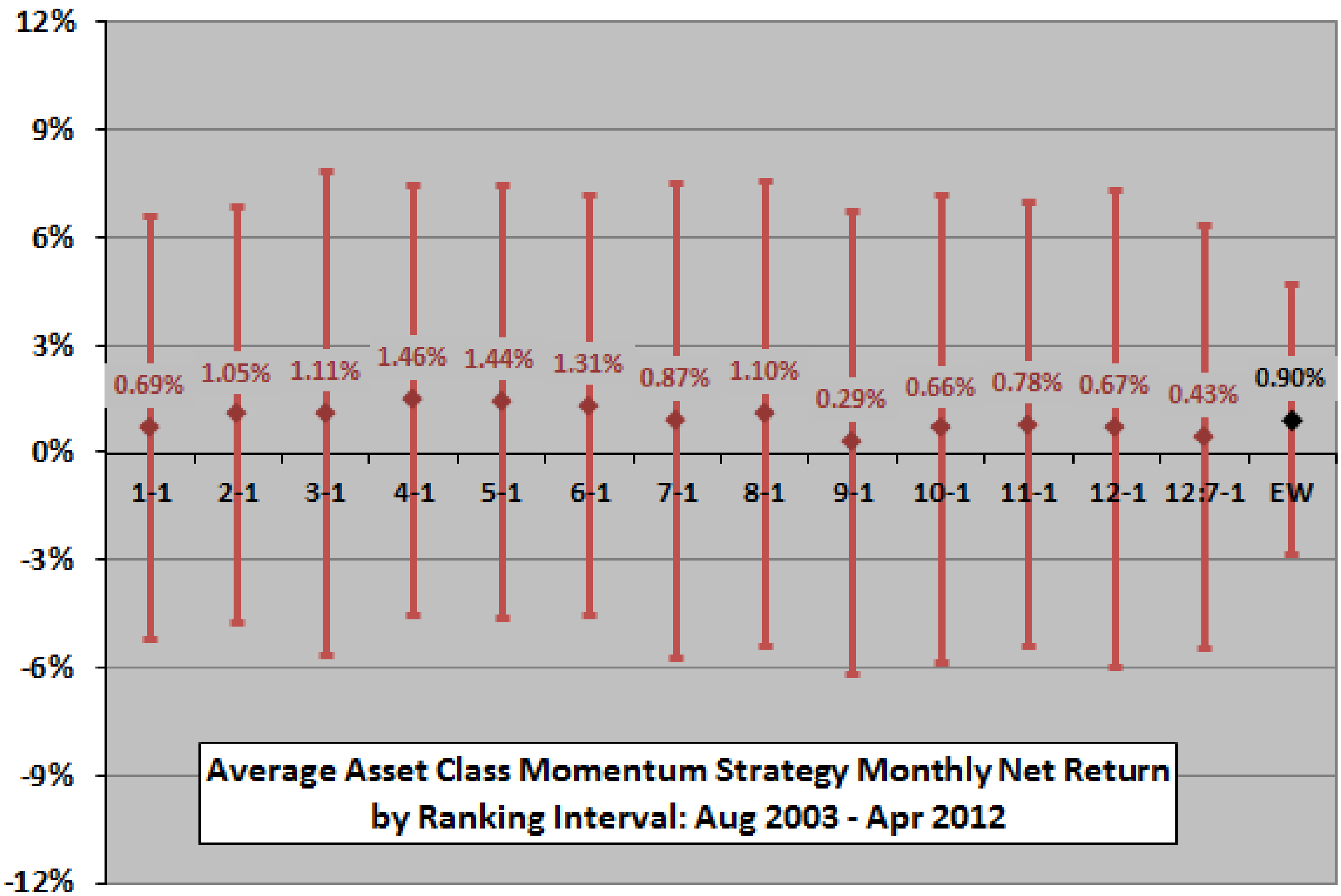
The next chart shows average monthly net returns for asset class momentum strategies 1-1 through 12-1 and 12:7-1 since August 2003 (allowing a 12-month return calculation for at least six ETFs, adding assets as they become available). The assumed level of trading (ETF switching) friction is 0.25% of the balance for all ranking intervals. Monthly EW portfolio rebalancing is frictionless for conservative benchmarking. Results suggest that:

- Ranking intervals of four, five and six months best fit multiple financial markets over the available sample period.
- Ranking intervals of more than eight months, including 12:7-1, do not work well.
- Variation across ranking intervals is not obviously systematic, undermining belief in a stable best choice.

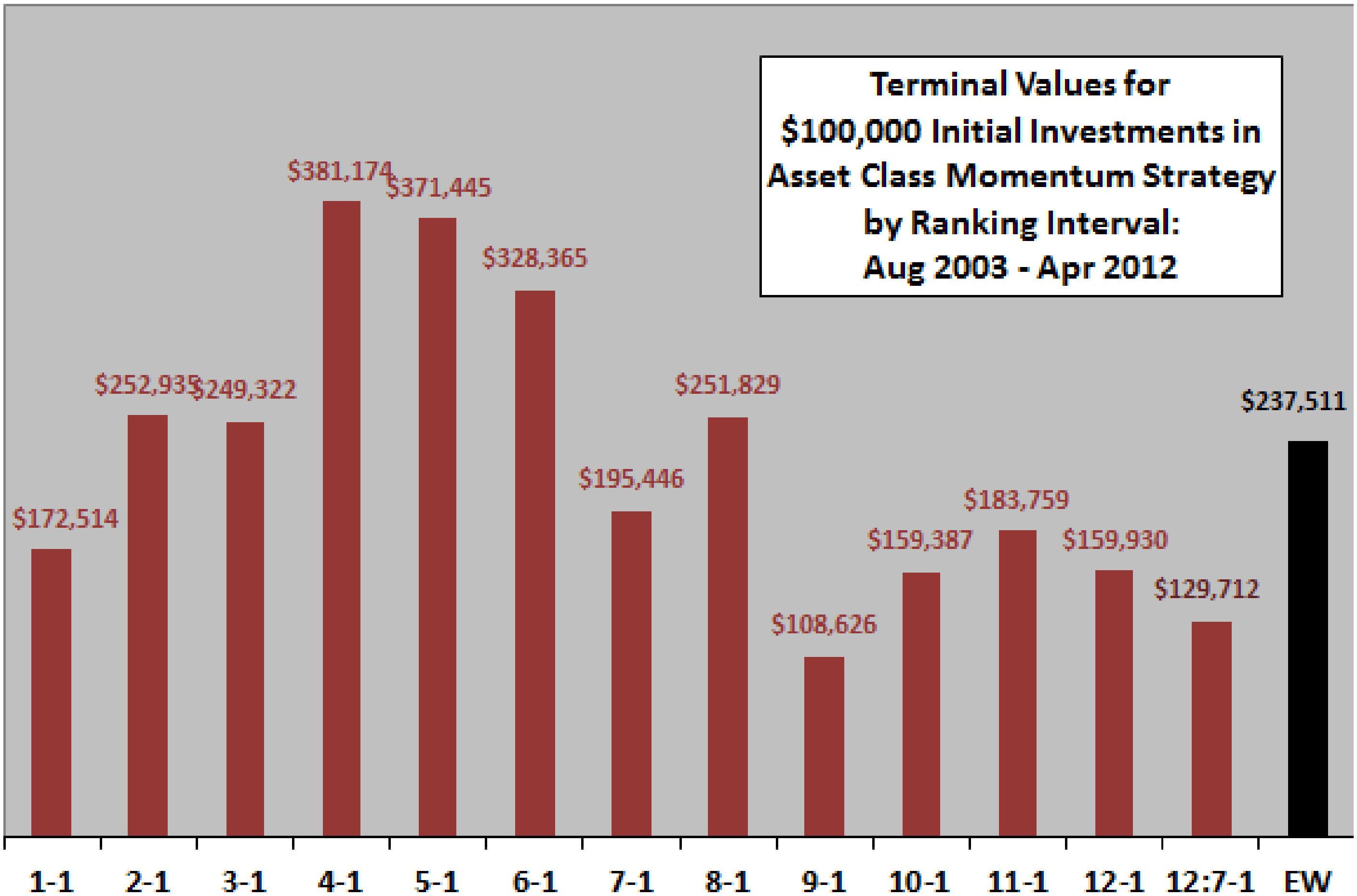
The available sample period is very short for confident inference. For example:

> It is plausible that the rate of change of economic/financial variables and the speed of trader reactions vary over time (whether somewhat predictably or randomly), such that different ranking intervals work better over different sample periods.
>
> It is also plausible that changes and trader reactions vary across asset classes. Comparing results with those in "Simple Sector ETF Momentum Strategy Robustness/Sensitivity Tests" (for a longer sample period) suggests a longer cycle for equity sector rotation than for asset class rotation.

For another perspective, we look at terminal values of equal investments across ranking intervals.



The final chart summarizes terminal values of $100,000 initial investments for asset class momentum strategies 1-1 through 12-1 and 12:7-1 since July 2003. Results generally confirm that ranking intervals of four, five and six months work best over the past few years. None of the ranking intervals lose money.



In summary, *evidence from momentum rank and ranking interval sensitivity tests based on very small sample offer little support for belief in simple asset class ETF momentum strategy reliability. In the available sample, selecting the top two ranks based on a ranking interval of four to six months is among the best alternatives.*

Cautions regarding findings include:

- The performance of the best (worst) ranking/ranking interval incorporates data snooping bias and therefore likely overstates (understates) expected performance.
- As noted, sample sizes (only about 20 independent six-month ranking intervals in the first test and about 10 independent 12-month ranking intervals in the second test) are very small for confident inference.
- Differences in results here from those in "Simple Sector ETF Momentum Strategy Robustness/Sensitivity Tests" and "Doing Momentum with Style (ETFs) Robustness/ Sensitivity Tests" (for longer sample periods) undermine belief in any pervasively optimal momentum strategy parameters.
- The method/parameters derive from research on individual stocks. While arguable that the findings should carry over to ETFs, there might be confounding effects. For example, hedging practices (using an asset class ETF to hedge positions in individual assets from the sector) might affect translation of an anomaly from individual assets to ETFs.
- To the extent return distributions are wild rather than normal, average returns and standard deviations of returns lose meaning as estimators of future returns.

Originally published at http://www.cxoadvisory.com/19039/momentum-investing/simple-asset-class-etf-momentum-strategy-robustnesssensitivity-tests/ on May 9, 2012.

Simple Asset Class ETF Momentum Strategy

May 9, 2012

Does a simple momentum strategy applied to tradable asset class proxies produce attractive results? To investigate, we test a simple strategy on the following eight asset class exchange-traded funds (ETF), plus cash:

PowerShares DB Commodity Index Tracking (DBC)
iShares MSCI Emerging Markets Index (EEM)
iShares MSCI EAFE Index (EFA)
SPDR Gold Shares (GLD)
iShares Russell 1000 Index (IWB)
iShares Russell 2000 Index (IWM)
SPDR Dow Jones REIT (RWR)
iShares Barclays 20+ Year Treasury Bond (TLT)
3-month Treasury bills (Cash)

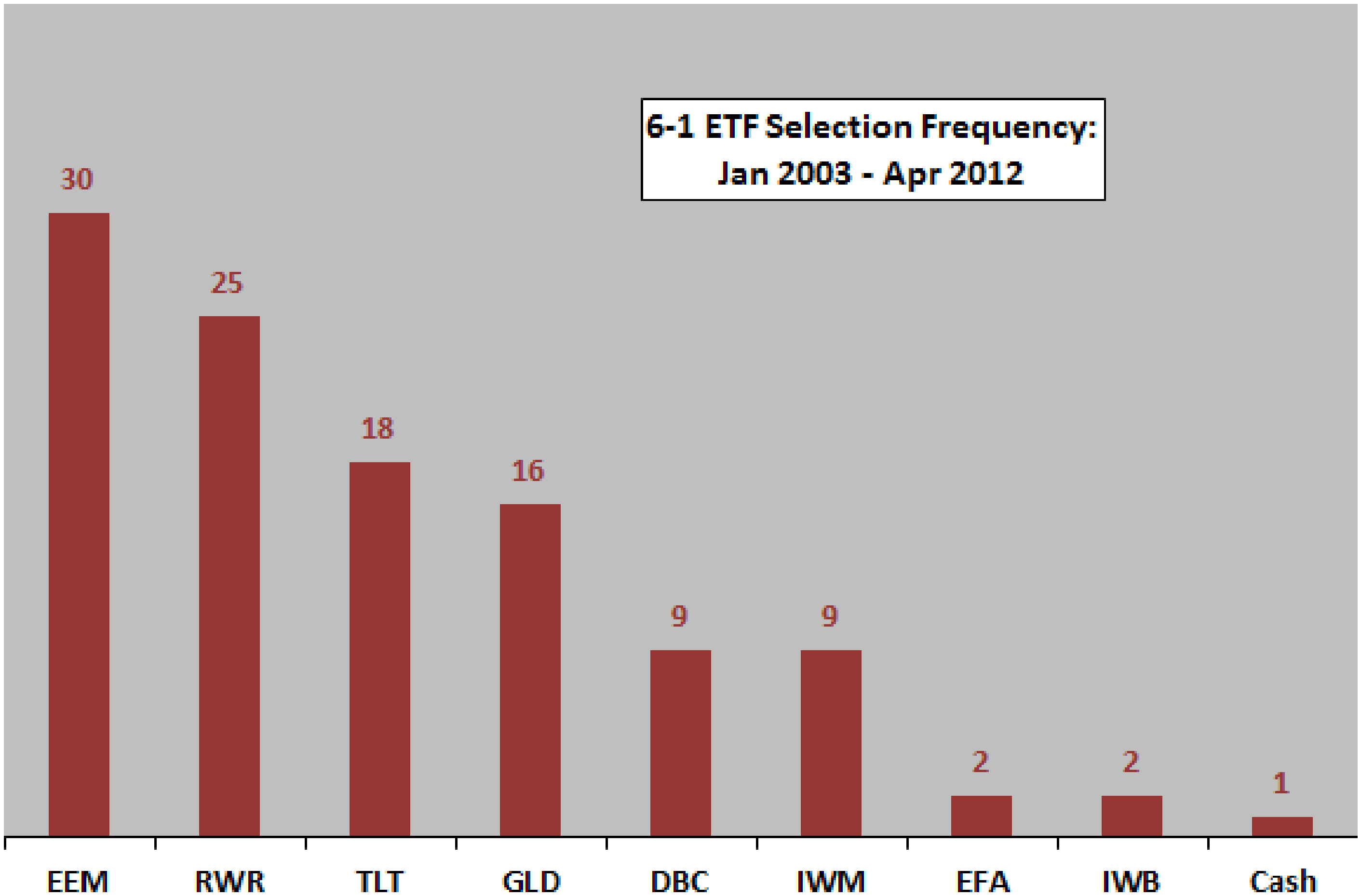
We allocate all funds at the end of each month to the asset class ETF or cash with the highest total return over the past six months (6-1). A six-month ranking period is intuitively large enough to gauge class momentum but small enough to react to changes in economic conditions that might favor one class over others. Using monthly adjusted closing prices for the asset class proxies and the yield for Cash over the period July 2002 (or inception if not available then) through April 2012 (118 months), *we find that:*

The following chart shows the distribution of asset class ETF winners based on past six-month total return over the entire sample period. Note that number of ETFs in competition increases over time, as follows:

- EFA, IWB, IWM, RWR and TLT are available over the entire sample period.
- EEM is available starting April 2003.
- GLD is available starting November 2004.
- DBC is available starting February 2006.

Results suggest that large-capitalization equity classes and Cash add little value to the 6-1 strategy.

How do the winning ETFs translate into 6-1 strategy cumulative returns?

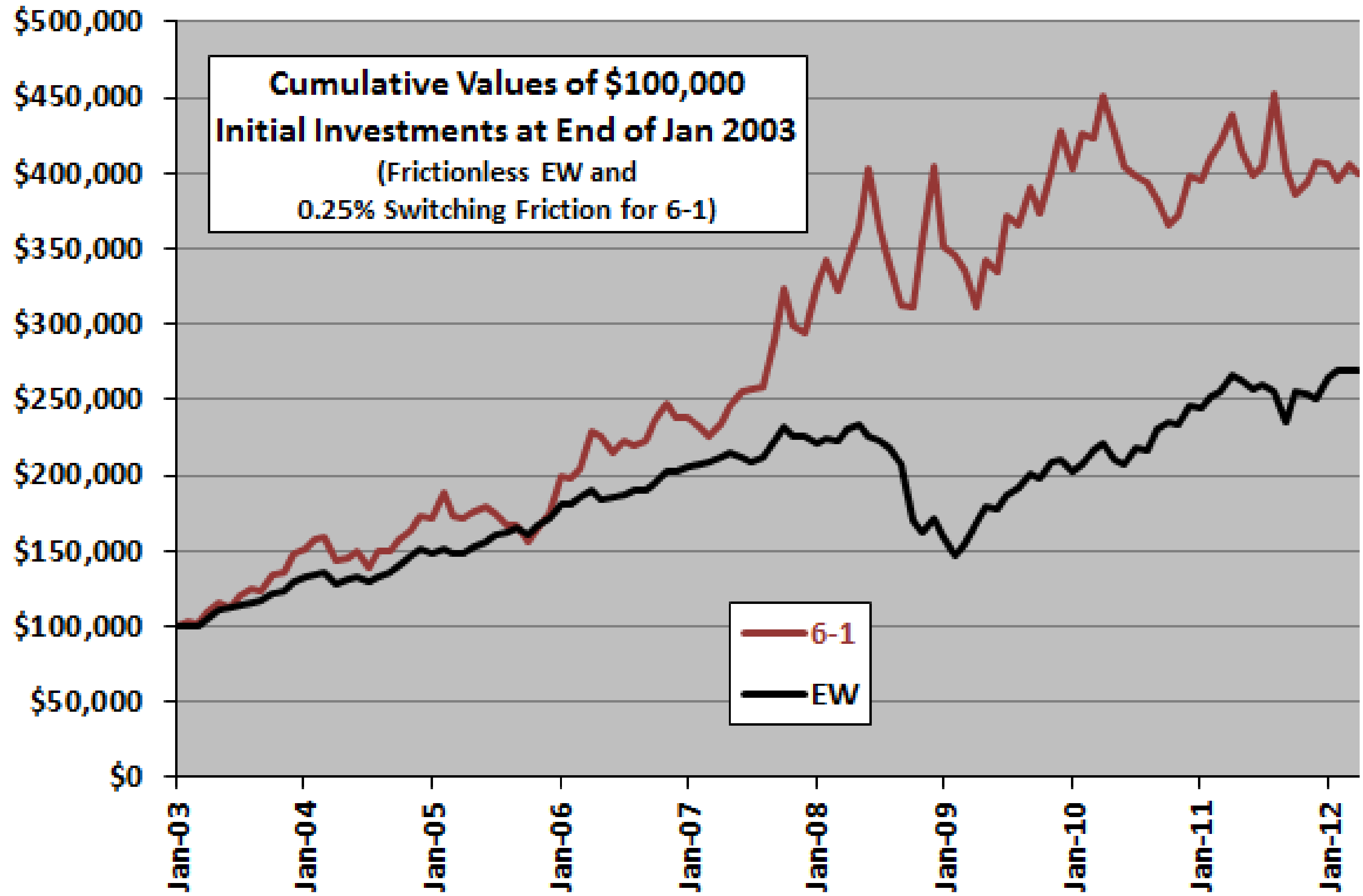


The next chart compares the cumulative values of $100,000 initial investments in the 6-1 strategy and an equally weighted, monthly rebalanced combination of the nine classes as available over the sample period (EW). Calculations derive from the following assumptions:

- Reallocate/rebalance at the close on the last trading day of each month (assume that total six-month past returns for the ETFs can be calculated just before the close).
- Trading (switching) friction for the 6-1 strategy is 0.25% of the balance whenever there is a change in holdings.
- Monthly rebalancing of the EW benchmark is frictionless, conservatively benchmarking the 6-1 strategy.
- Ignore any tax implications of trading.

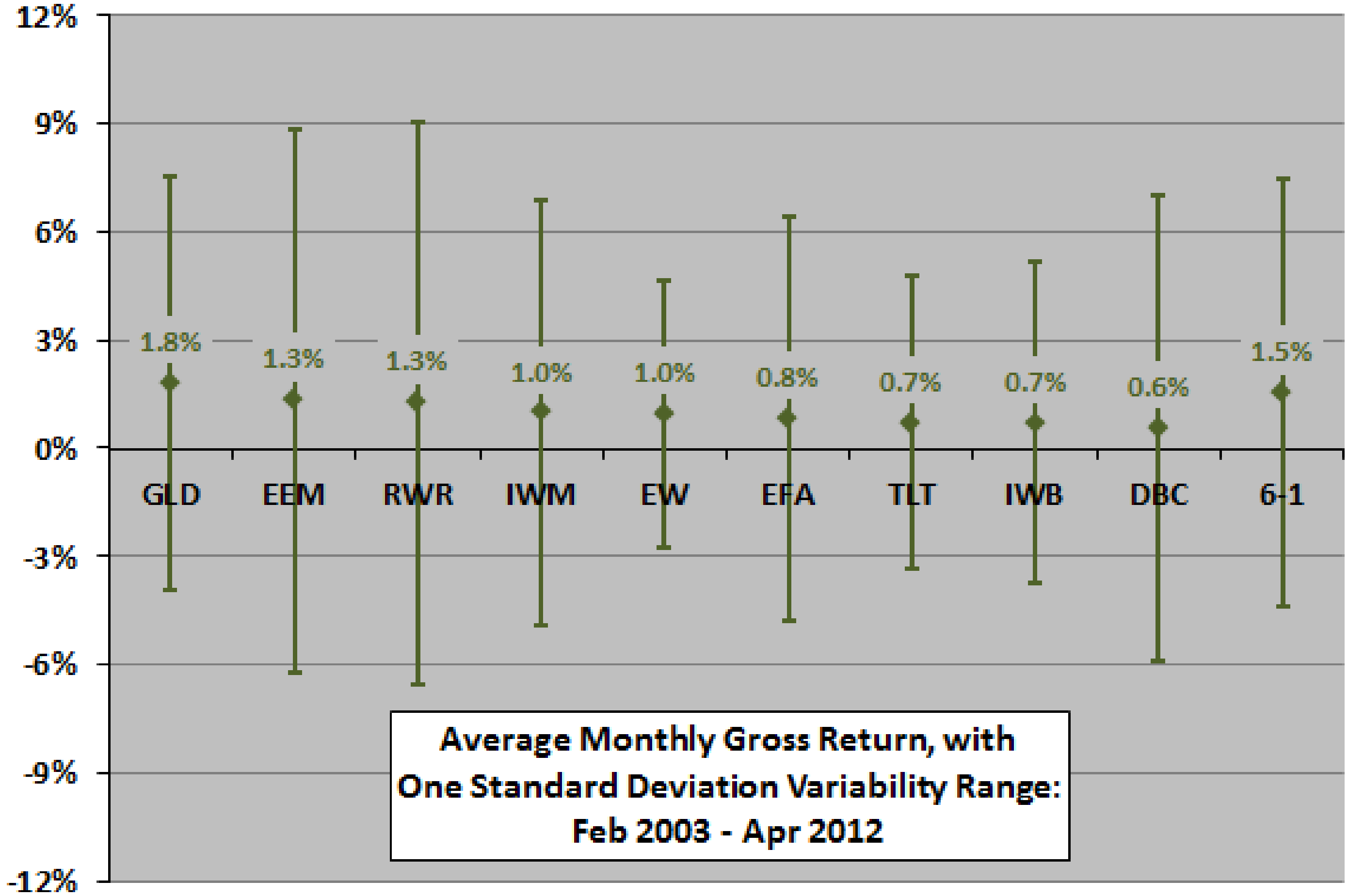
At the assumed level of switching friction, the 6-1 strategy outperforms EW fairly consistently, but with higher volatility. In short, the 6-1 strategy adds value to simple diversification.

How do average monthly returns, as alternative measures of performance, compare?



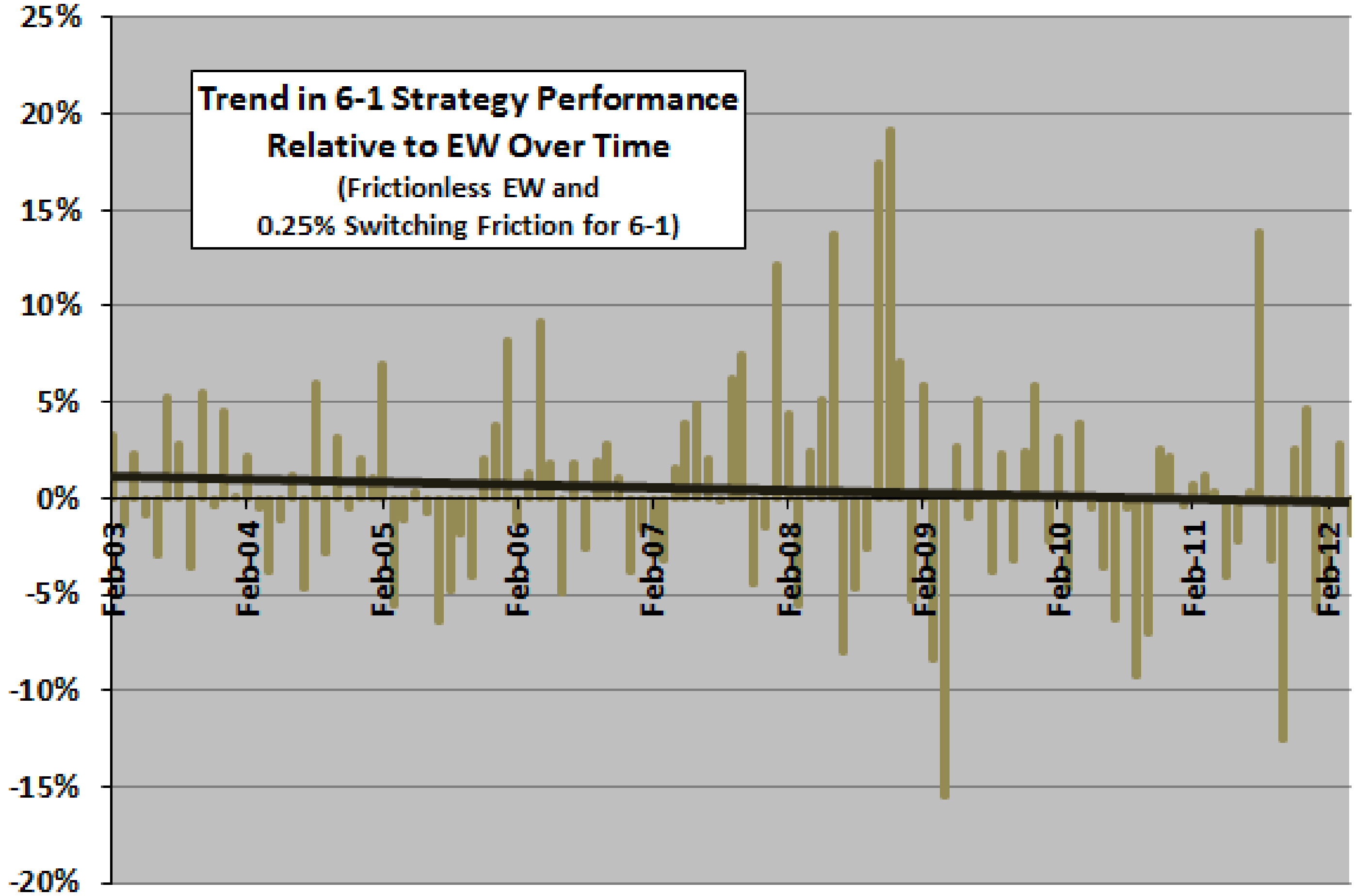
The next chart depicts the average monthly <u>gross</u> returns (no switching friction) and the standard deviations of monthly returns for the 6-1 momentum strategy, the EW benchmark and all component ETFs (but not Cash). Results suggest that the 6-1 momentum strategy outperforms all components except GLD (but comparison can mislead due to different introduction dates for some ETFs, including GLD).

Is the momentum effect consistent over time?



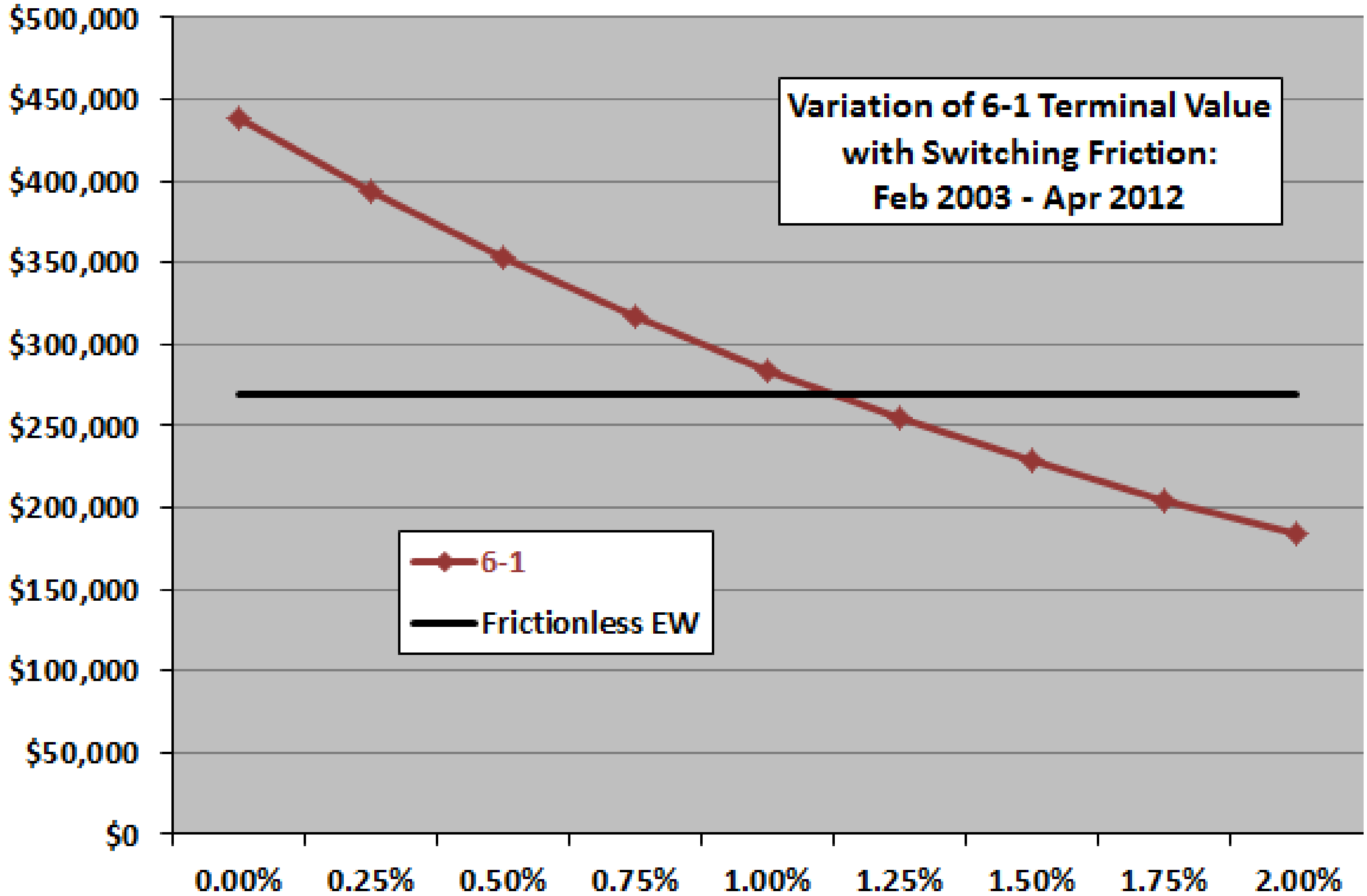
The next chart shows the monthly net returns for the 6-1 strategy relative to the frictionless EW benchmark over the entire sample period, along with a best-fit trend line. Results indicate that the outperformance of the momentum strategy relative to equal weighting dissipates over time, perhaps because of growing use/market adaptation. However, the sample period is short and monthly relative returns highly variable.

How sensitive is the performance of the 6-1 strategy to level of switching friction?



The next chart plots the terminal value of the 6-1 strategy for switching frictions ranging from 0.00% to 2.00% of the balance over the sample period. It also shows the frictionless EW terminal value as a benchmark. Results indicate that the EW benchmark is easily beatable for most investors.

How does the 6-1 strategy applied to asset classes compare with the best strategies of "Simple Sector ETF Momentum Strategy" and "Doing Momentum with Style (ETFs)"?



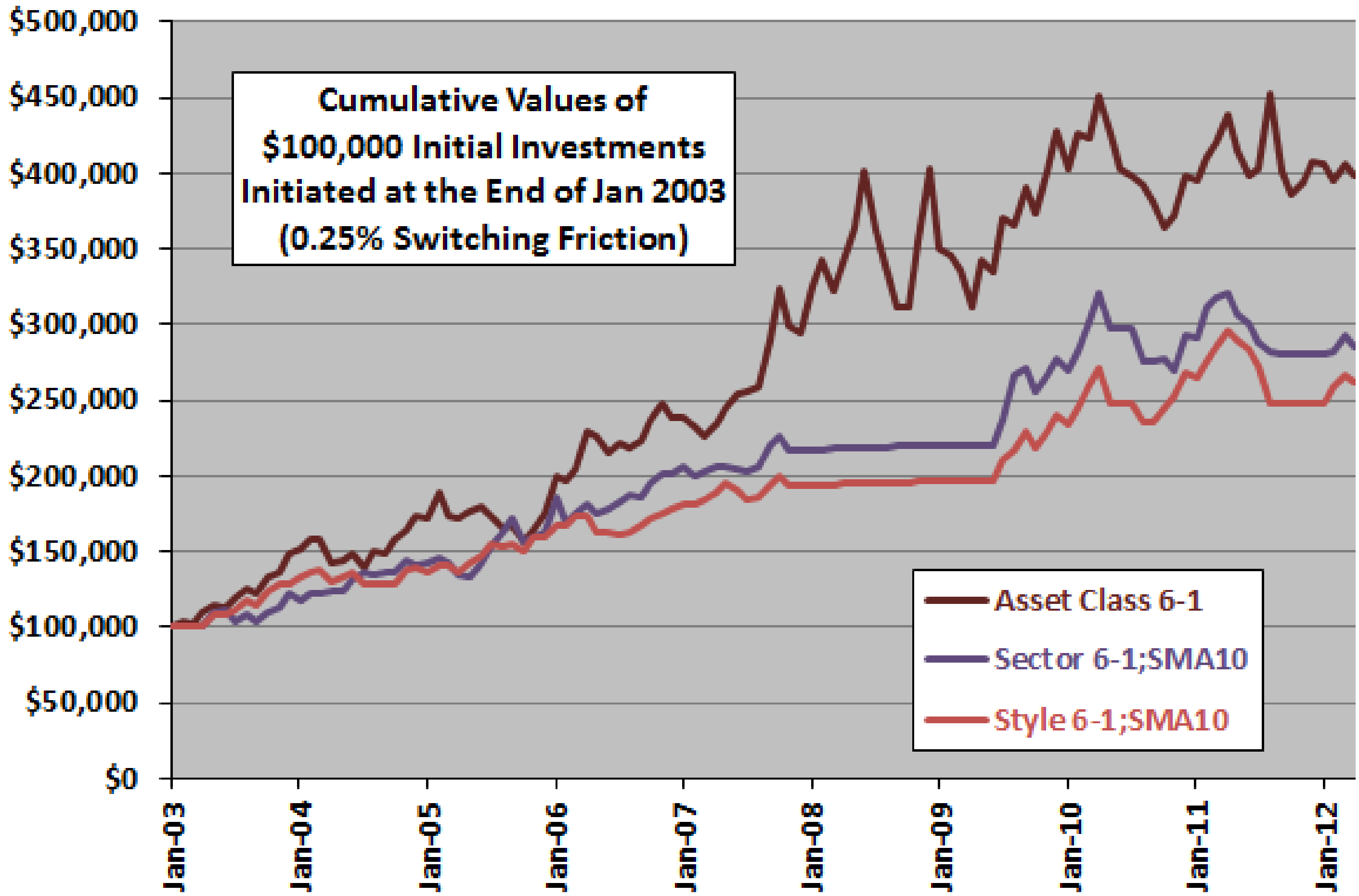
The final chart compares cumulative values of $100,000 initial investments in the 6-1 asset class ETF momentum strategy, the 6-1;SMA10 sector ETF momentum strategy and the 6-1; SMA10 style ETF momentum strategy over the available overlapping sample period (from the end of January 2003), with switching friction set at 0.25%. The latter two strategies invest each month in the six-month past return winner among nine sector ETFs and among six style ETFs, respectively, or cash depending on whether the S&P 500 Index is above or below its 10-month simple moving average.

The 6-1 asset class momentum strategy generally beats the other two, but with higher volatility.

Average monthly net returns and standard deviations of monthly returns:

- 6-1 asset class ETF momentum strategy: 1.43% and 5.92%, with risk-return ratio 0.24.
- 6-1;SMA10 sector ETF momentum strategy: 1.03% and 4.11%, with risk-return ratio 0.25.
- 6-1;SMA10 style ETF momentum strategy: 0.92% and 3.26%, with risk-return ratio 0.28.

The number of switches for the three strategies are 45, 39 and 37, respectively, so lowering the switching friction favors the asset class strategy performance.



In summary, *evidence from a limited sample period suggests that a simple asset class ETF momentum strategy beats an equal-weighted benchmark over the past nine years under conservative assumptions, adding value to simple diversification, but the added value may be dissipating.*

For robustness tests, see "Simple Asset Class ETF Momentum Strategy Robustness/Sensitivity Tests".

Cautions regarding findings include:

- Sample size is modest (about 20 independent six-month momentum ranking intervals for five ETFs and fewer for three others).
- The selected ETF ranking interval derives from prior academic studies that most often use six-month and 12-month ranking intervals, with one-month holding intervals. This prior research may impound (and therefore transmit) data snooping bias, which is especially pernicious for small samples. Ranking intervals other than six months and holding periods other than one month may produce different results. For the above tests, using longer ranking and holding intervals would effectively reduce the already-small sample size. Optimizing the ranking and holding intervals would elevate data snooping bias.
- Potential wildness in ETF monthly return distributions limits confidence in results.

Originally published at http://www.cxoadvisory.com/18886/momentum-investing/simple-asset-class-etf-momentum-strategy-performance/ on May 9, 2012.

Doing Momentum with Style (ETFs) Robustness/ Sensitivity Tests

May 8, 2012

How sensitive is the performance of "Doing Momentum with Style (ETFs)" to selecting ranks other than winners and to choosing a momentum ranking interval other than six months? This strategy each month ranks the following six style exchange-traded funds (ETF) on past return and rotates to the strongest style:

iShares Russell 1000 Value Index (IWD) – large capitalization value stocks.
iShares Russell 1000 Growth Index (IWF) – large capitalization growth stocks.
iShares Russell Midcap Value Index (IWS) – mid-capitalization value stocks.
iShares Russell Midcap Growth Index (IWP) – mid-capitalization growth stocks.
iShares Russell 2000 Value Index (IWN) – small capitalization value stocks.
iShares Russell 2000 Growth Index (IWO) – small capitalization growth stocks.

Available data are so limited that sensitivity test results may mislead. With that reservation, we perform two robustness/sensitivity tests: (1) comparison of returns for all six ranks of winner through loser based on a ranking interval of six months and a holding interval of one month (6-1); and, (2) comparison of winner returns for ranking intervals ranging from one to 12 months (1-1 through 12-1) and for a six-month lagged six-month ranking interval (12:7-1) per "Isolating the Decisive Momentum (Echo?)", all with one-month holding intervals. Using monthly adjusted closing prices for the style ETFs and SPDR S&P 500 (SPY) over the period August 2001 through April 2012 (129 months), *we find that:*

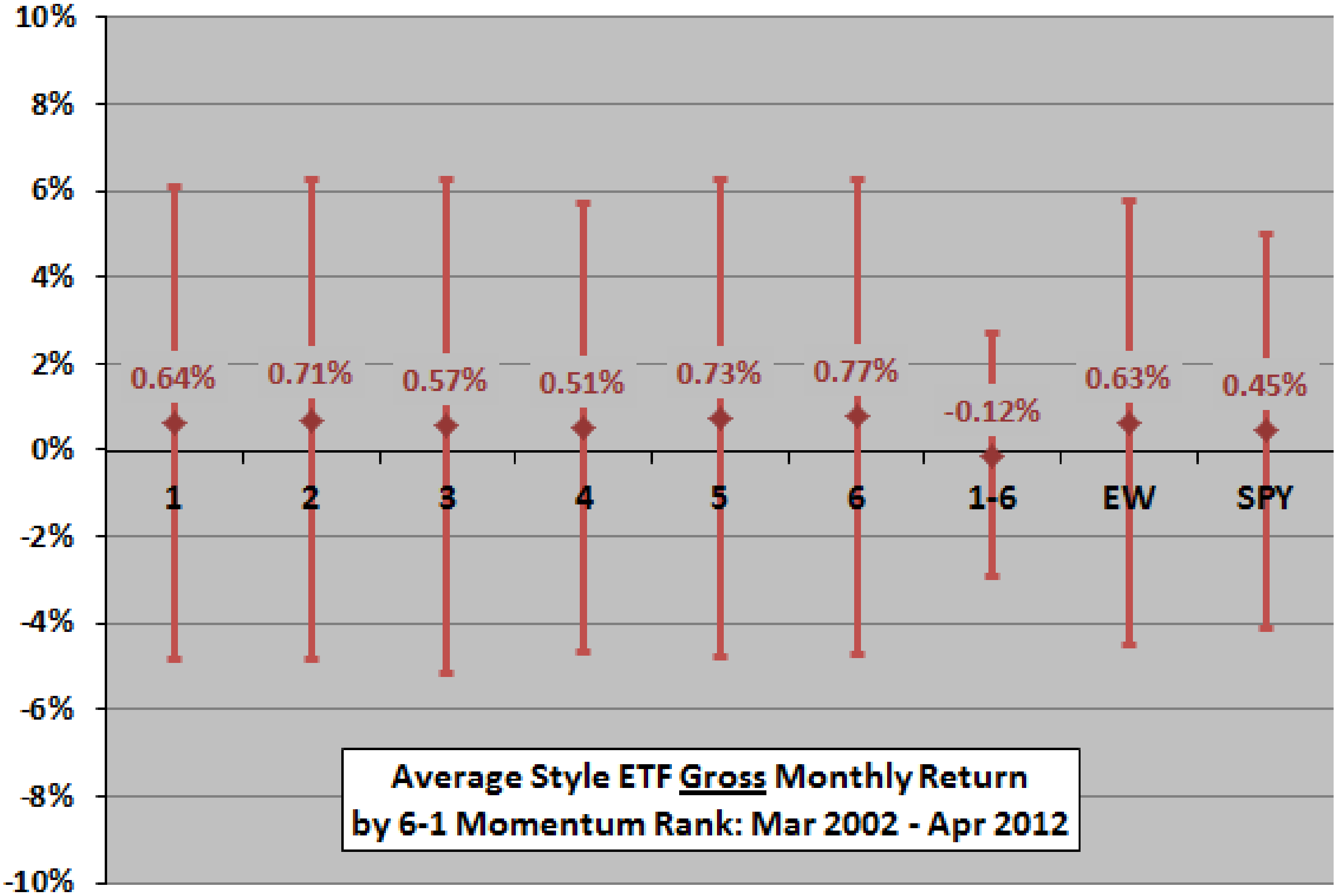
All calculations assume that monthly reallocation/rebalancing occurs at the close on the last trading day of each month (assuming that past returns for the ETFs can be calculated for ranking purposes just before the close).

The following chart shows average monthly 6-1 style momentum strategy gross returns for rank 1 (highest momentum) through rank 6 (lowest momentum) since March 2002, with one standard deviation variability ranges. The chart also shows comparable statistics for an equally weighted, monthly rebalanced (EW) portfolio of the six styles as a simple benchmark (representing the value of diversification) and for SPY. Notable points are:

- Rank 1 statistics are barely different from those for the EW portfolio, and the difference in average returns between ranks 1 and 6 is negative.
- Average returns do not decline systematically from rank 1 through rank 6. In fact, ranks 5 and 6 have higher average returns than ranks 1, 3 and 4.

Results provide no support for belief in style momentum strategy usefulness relative to the simple diversification benefit of the EW portfolio.

What happens for ranking intervals other than six months?

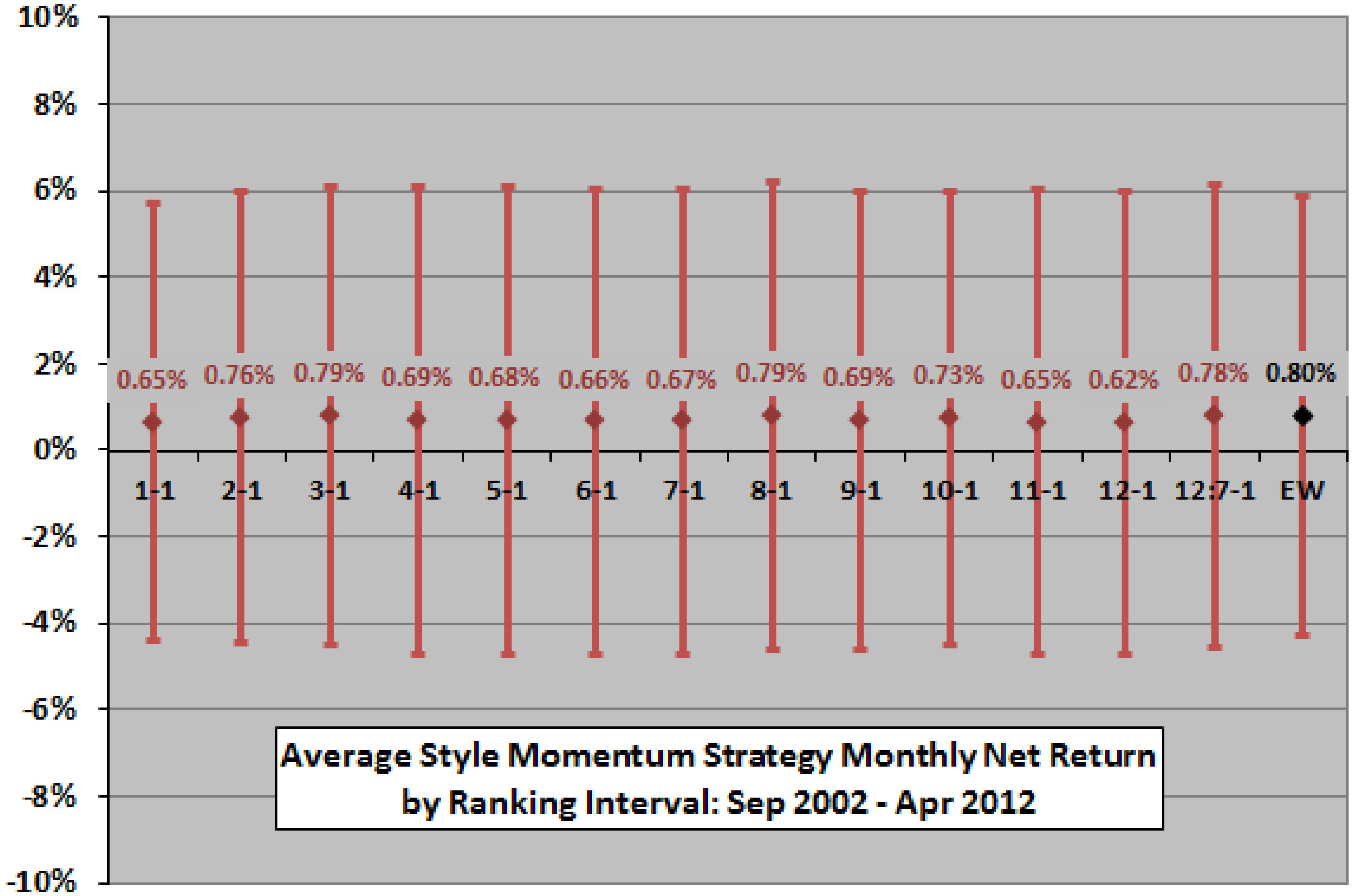


The next chart shows average monthly net returns for style momentum strategies 1-1 through 12-1 and 12:7-1 since September 2002 (allowing a 12-month return calculation). The assumed level of trading (switching) friction is 0.25% of the balance for all ranking intervals. Monthly EW portfolio rebalancing is frictionless for conservative benchmarking. Results suggest that:

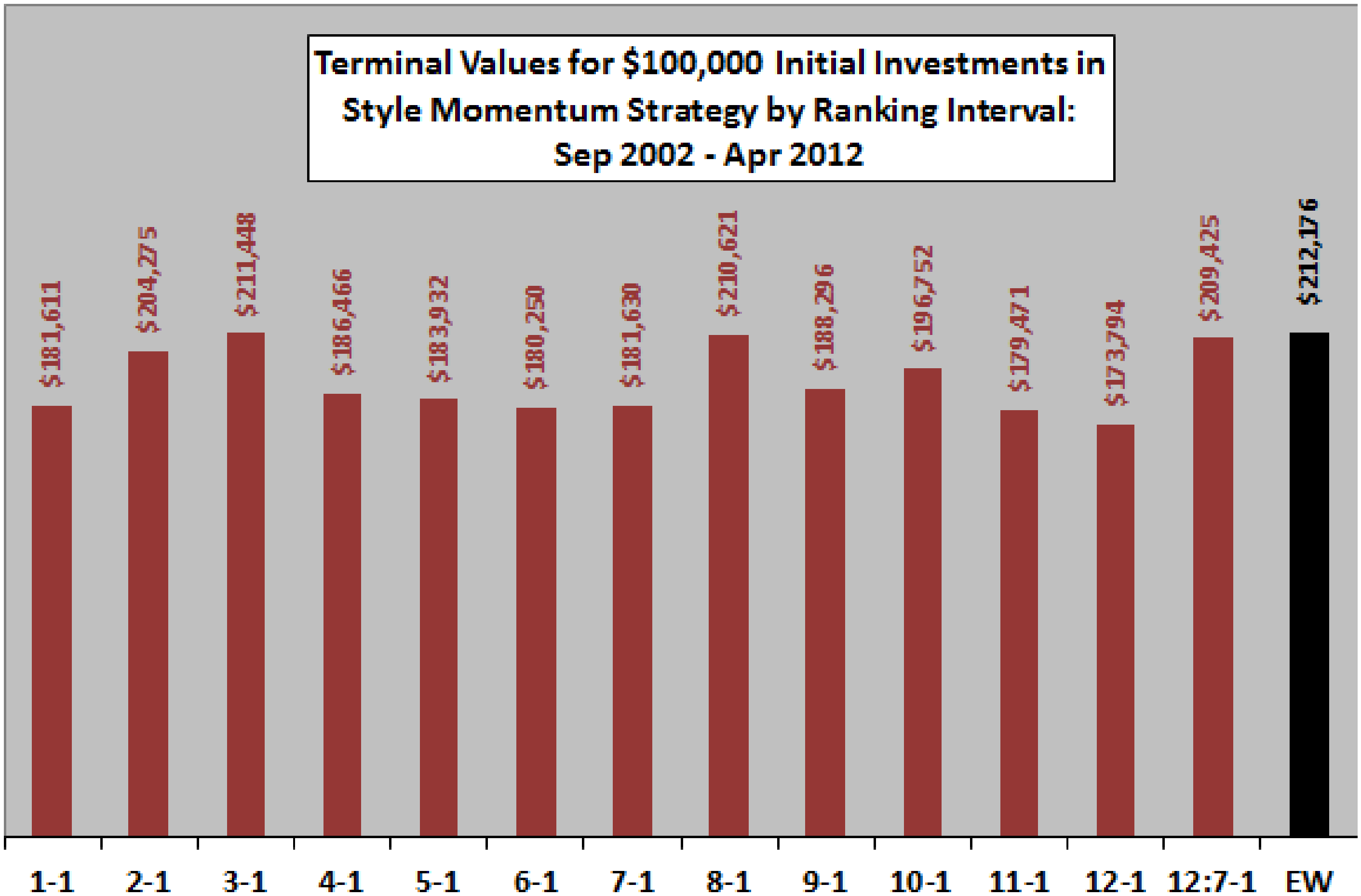
- Ranking intervals of two, three and eight months, and 12:7 (six months lagged six months), best fit U.S. equity styles over the available sample period. Six-month and 12-month ranking intervals are not among the best.
- Variation across ranking intervals is not systematic, undermining belief in a stable best choice.

The available sample period is short for confident inference. The best ranking intervals may be lucky rather than fundamentally meaningful.

For another perspective, we look at terminal values of equal investments across ranking intervals.



The final chart summarizes terminal values of $100,000 initial investments for style momentum strategies 1-1 through 12-1 and 12:7-1 since December 1999. Results generally confirm that ranking intervals of two, three, eight and 12:7 months work best over the sample period. However, at the assumed level of trading friction, these choices do not beat the frictionless EW portfolio, which is slightly less volatile.



In summary, *evidence from momentum rank and ranking interval sensitivity tests for a limited sample offer no support for belief in simple sector ETF momentum strategy reliability or value in enhancing basic diversification.*

Results suggest that it is important to add a rule to avoid bear markets, such as the 10-month simple moving average signal described in "Doing Momentum with Style (ETFs).

Cautions regarding findings include:

- The performance of the best (worst) ranking/ranking interval incorporates data snooping bias and therefore likely overstates (understates) expected performance.
- As noted, sample sizes (only about 22 independent six-month ranking intervals in the first test and 11 independent 12-month ranking intervals in the second test) are very small for confident inference.
- Differences in results here from those in "Simple Sector ETF Momentum Strategy Robustness/Sensitivity Tests" (for a longer sample period) undermine belief in any pervasively optimal momentum strategy parameters.
- The method/parameters derive from research on individual stocks. While arguable that the findings should carry over to ETFs, there might be confounding effects. For example, hedging practices (using a style ETF to hedge positions in individual stocks) might affect translation of an anomaly from individual stocks to ETFs.
- To the extent return distributions are wild rather than normal, average returns and standard deviations of returns lose meaning as estimators of future returns.

Originally published at http://www.cxoadvisory.com/19129/size-effect/doing-momentum-with-style-etfs-robustnesssensitivity-tests/ on May 8, 2012.

Doing Momentum with Style (ETFs)

May 8, 2012

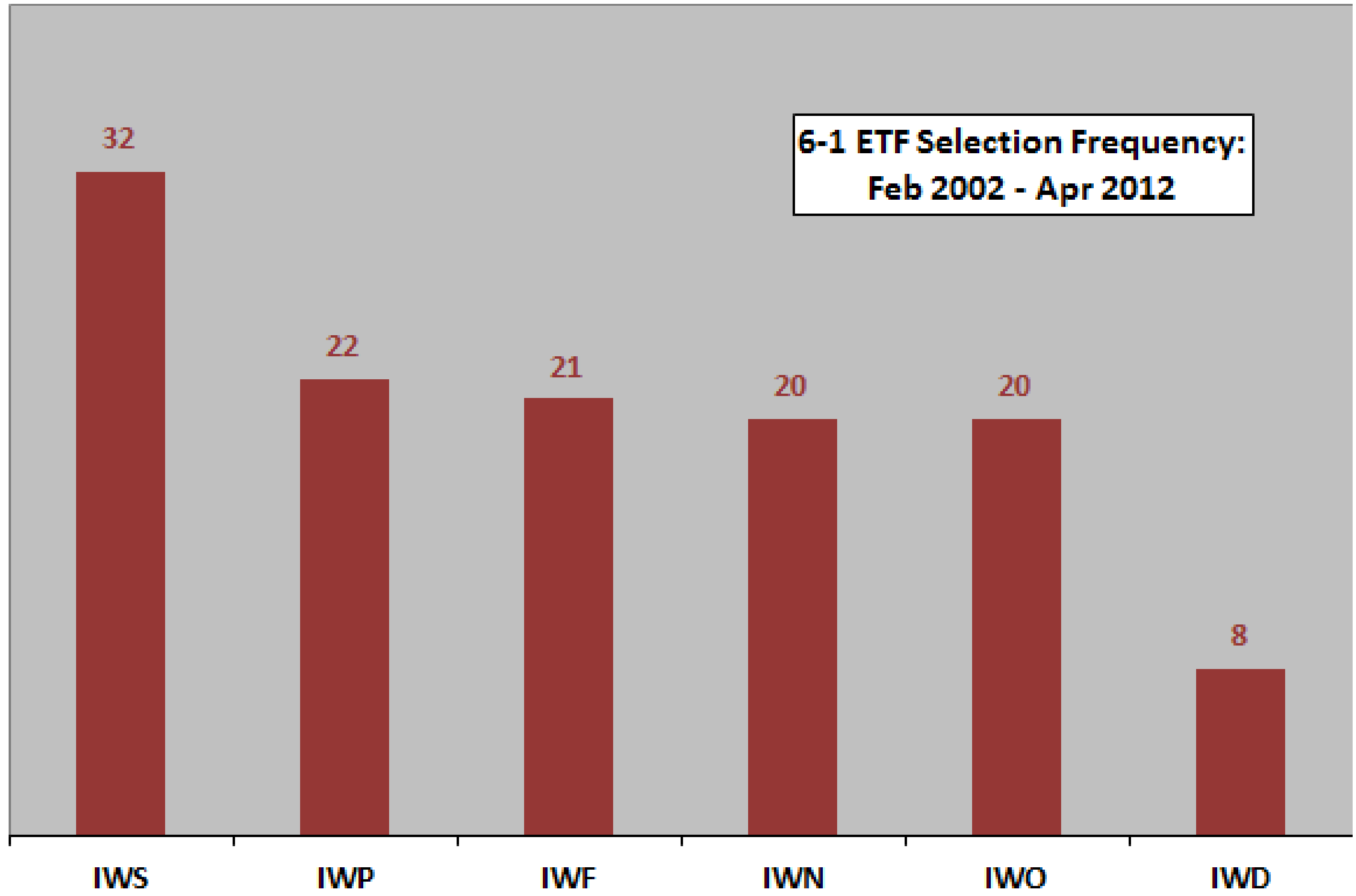
"Beat the Market with Hot-Anomaly Switching?" concludes that "a trader who periodically switches to the hottest known anomaly based on a rolling window of past performance may be able to beat the market. Anomalies appear to have their own kind of momentum." Does momentum therefore work for style-based exchange-traded funds (ETF)? To investigate, we apply a simple momentum strategy to the following six ETFs that cut across market capitalization (large, medium and small) and value versus growth:

iShares Russell 1000 Value Index (IWD) – large capitalization value stocks.
iShares Russell 1000 Growth Index (IWF) – large capitalization growth stocks.
iShares Russell Midcap Value Index (IWS) – mid-capitalization value stocks.
iShares Russell Midcap Growth Index (IWP) – mid-capitalization growth stocks.
iShares Russell 2000 Value Index (IWN) – small capitalization value stocks.
iShares Russell 2000 Growth Index (IWO) – small capitalization growth stocks.

The simple (6-1) strategy allocates all funds each month to the one style ETF with the highest total return over the past six months. A six-month ranking period is intuitively large enough to gauge style momentum but small enough to react to changes in business conditions that might favor one style over others. An alternative, more cautious strategy allocates at the end of each month all funds either to the style ETF with the highest total return over the past six months or to cash depending on whether the S&P 500 Index is above or below its 10-month simple moving average (6-1;SMA10). Using monthly adjusted closing prices for the style ETFs, the S&P 500 index, 3-month Treasury bills (T-bills) and S&P Depository Receipts (SPY) over the period August 2001 through April 2012 (129 months, limited by data for IWS and IWP), *we find that:*

The following chart shows the distribution of style ETF winners based on past six-month total return over the available sample period. The mid-capitalization value style comprises 32 of the 123 monthly winners (26%).

How does applying the 6-1 strategy translate into cumulative returns?

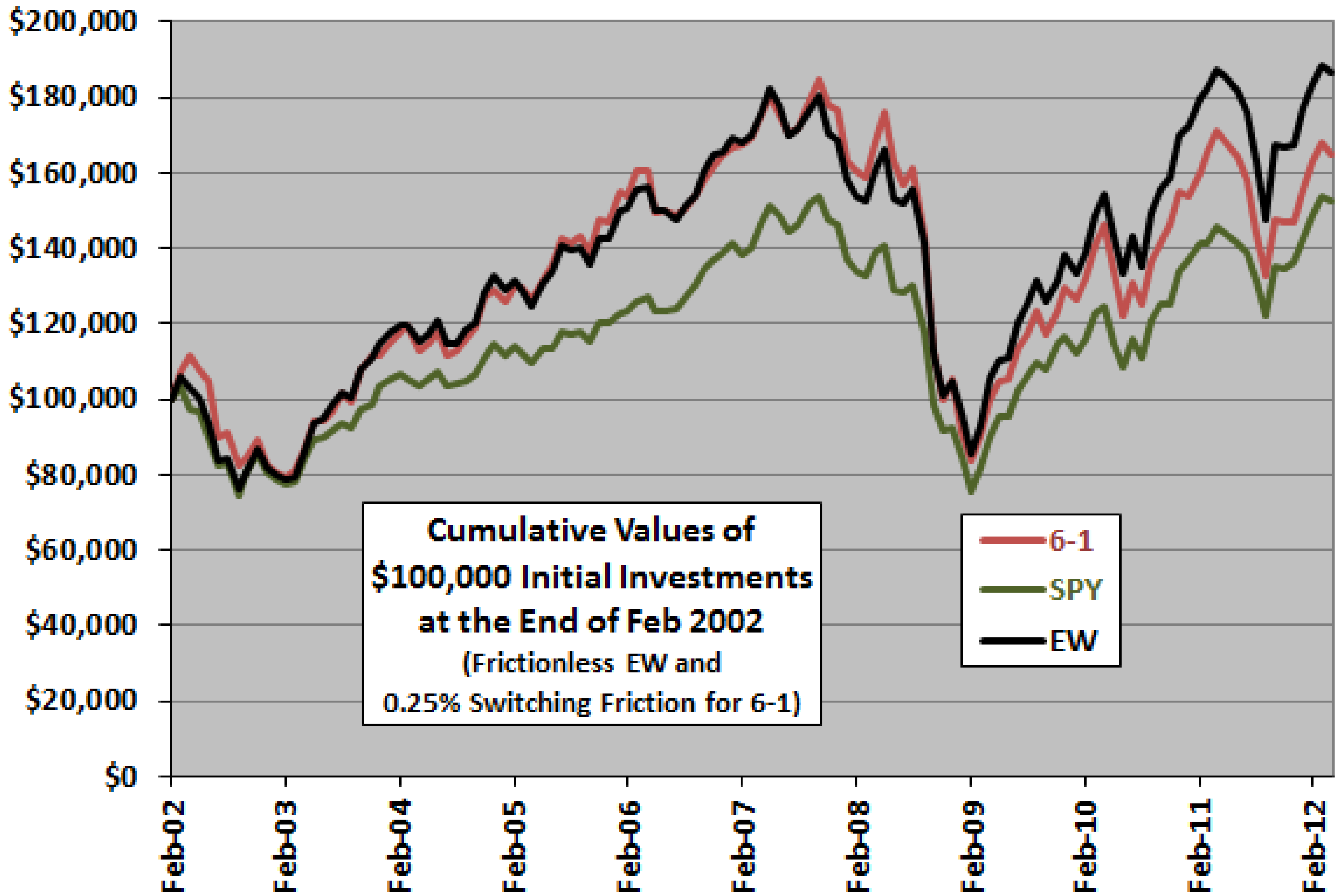


The next chart compares the cumulative values of $100,000 initial investments in the 6-1 strategy, SPY and an equally weighted portfolio of the style ETFs (EW), rebalanced monthly, over the available sample period. Calculations derive from the following assumptions:

- Reallocate/rebalance at the close on the last trading day of each month (assume that values and total six-month past returns for the ETFs can be calculated just before the close).
- Trading (switching) friction for the 6-1 strategy is 0.25% of the balance whenever there is a change in holdings, but EW portfolio rebalancing is frictionless, conservatively benchmarking the 6-1 strategy.
- Ignore any tax implications of trading.

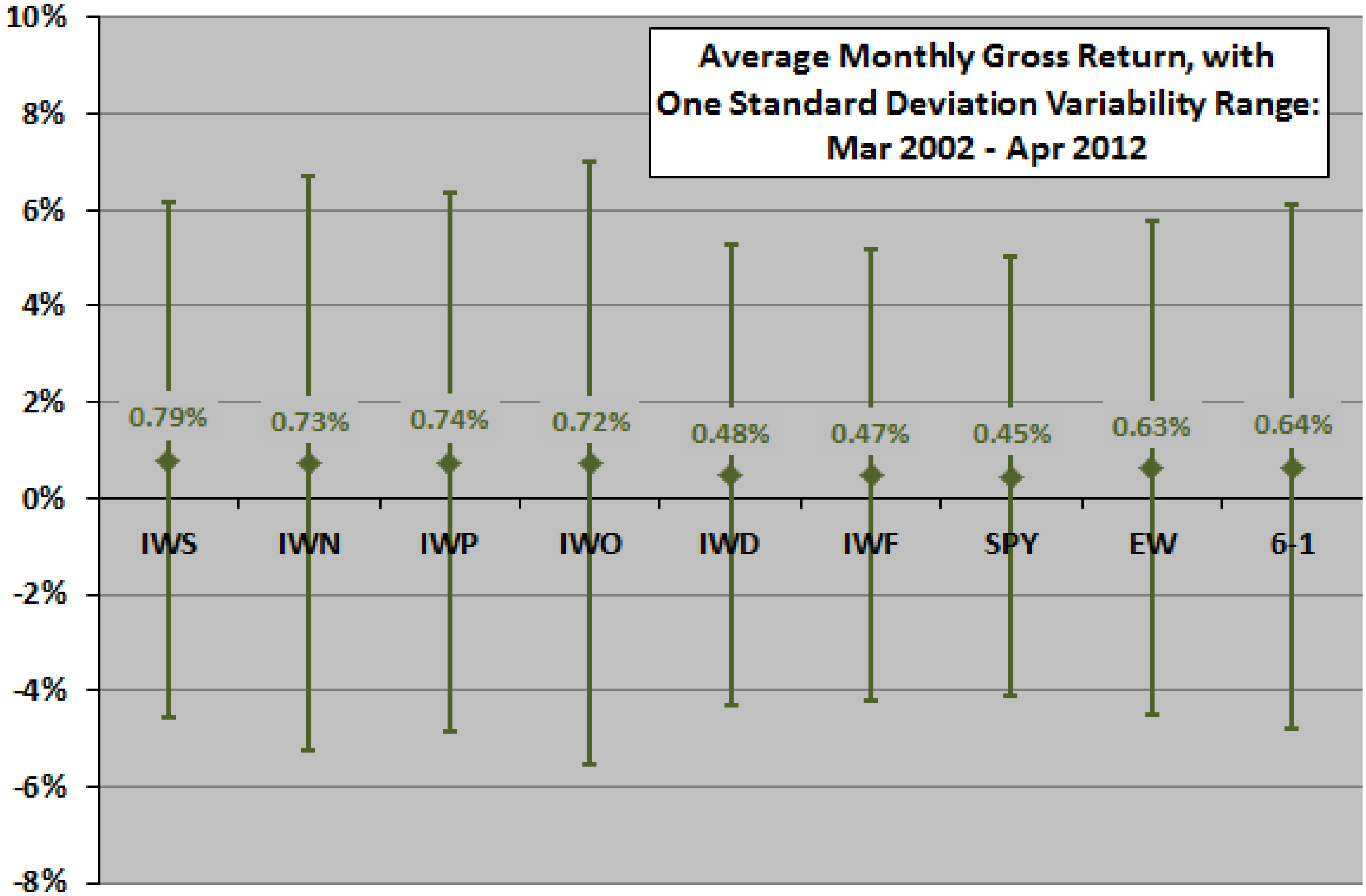
At the assumed level of switching friction, the 6-1 strategy beats SPY and is generally competitive with the EW portfolio. However, it does not beat the EW portfolio, undermining belief that the momentum strategy adds value to simple diversification.

How do average monthly returns, as alternative measures of strategy performance, compare?



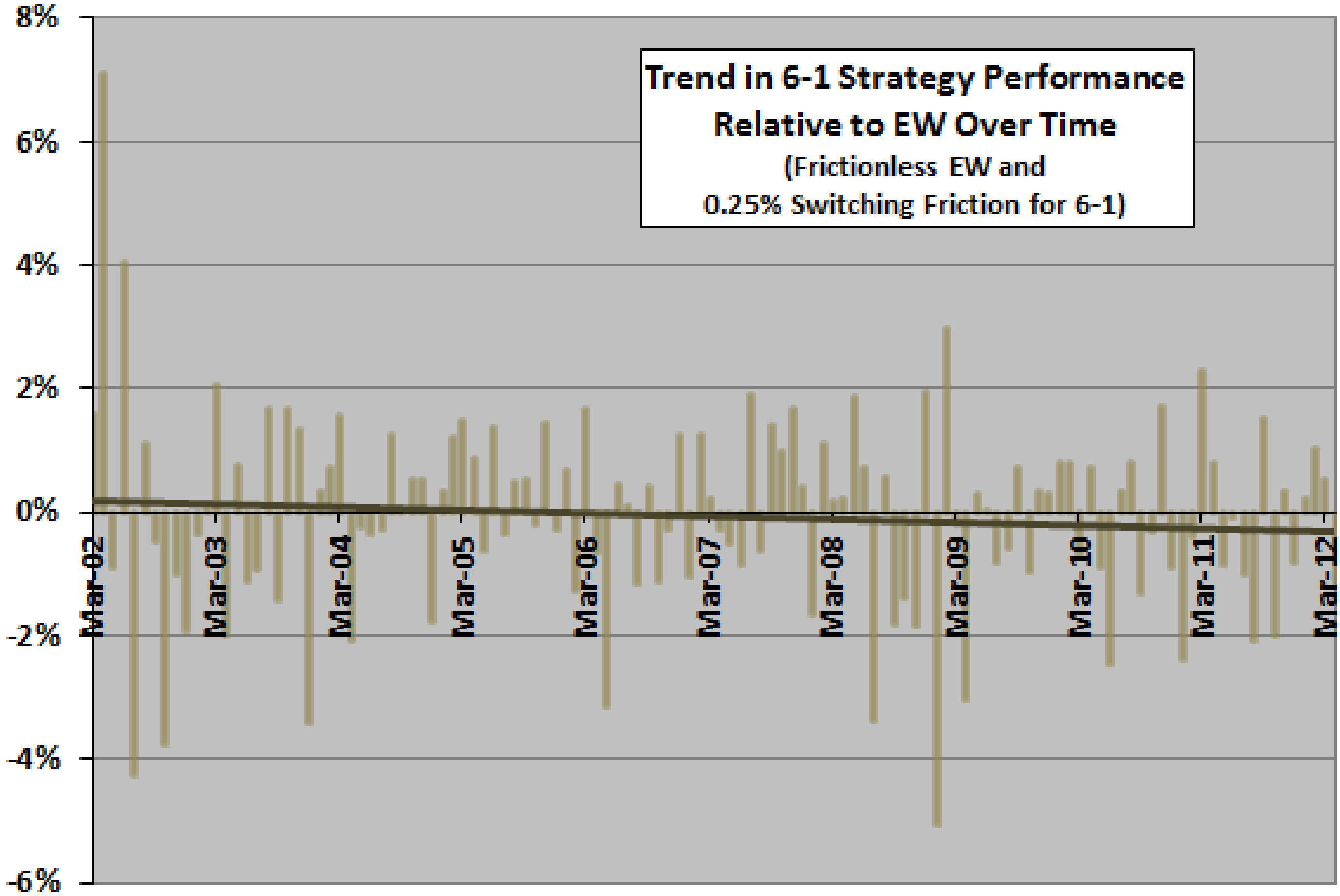
The next chart summarizes gross average (arithmetic mean) monthly returns and standard deviations of monthly returns for each of the style ETFs, SPY, the EW portfolio and the 6-1 strategy over the available sample period. The 6-1 strategy and the EW portfolio have similar statistics.

Is the performance of the 6-1 style strategy relative to the EW portfolio stable over time?



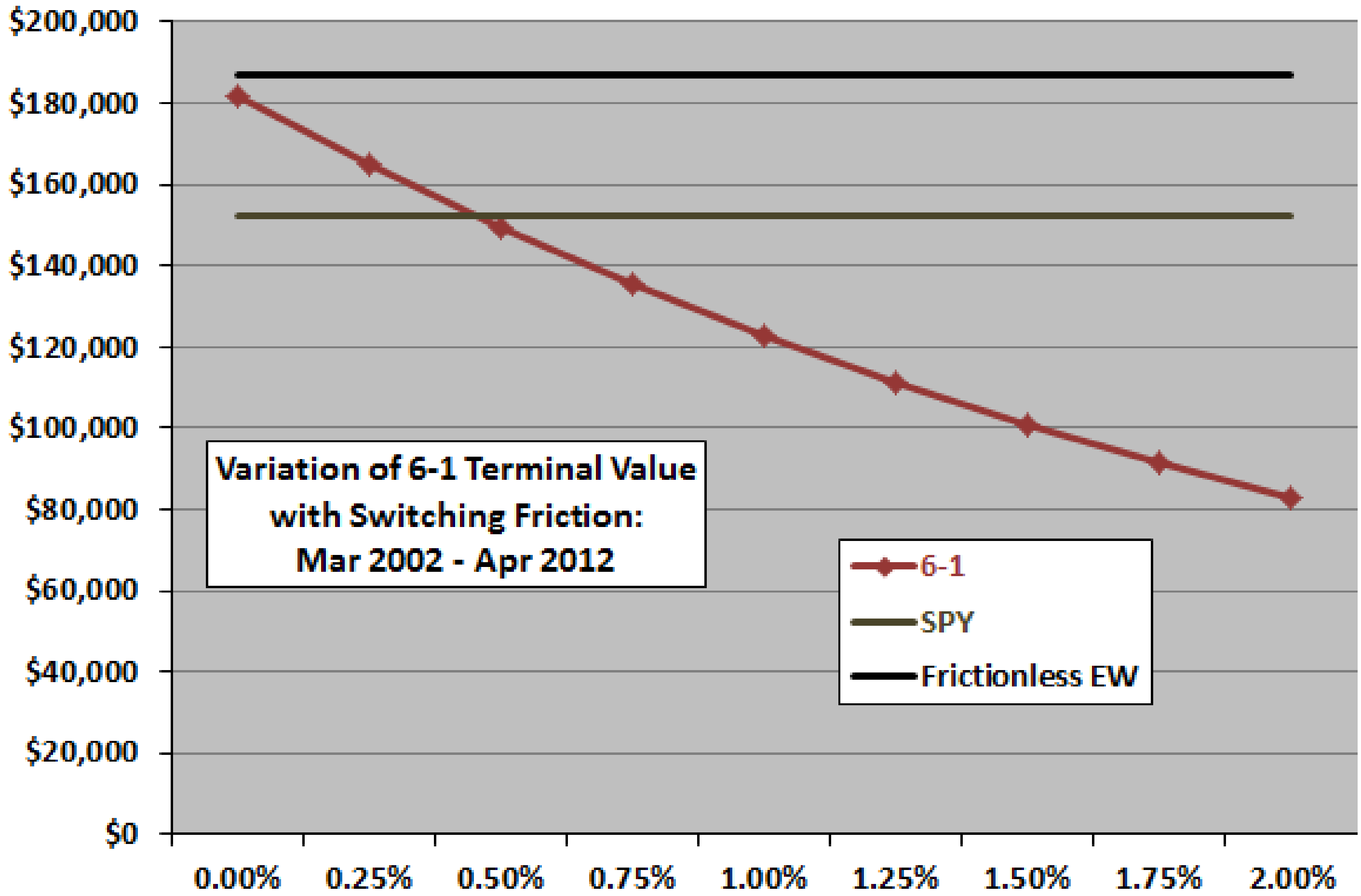
The next chart shows the net monthly return for the 6-1 strategy minus same-month EW portfolio return over the available sample period, along with a trend line. The trend line slopes downward into negative values, suggesting that the 6-1 strategy adds value to simple diversification early in the sample period but is a drag later. However, the sample period is short and monthly relative returns highly variable.

How does the terminal value of the 6-1 strategy vary with assumed level of switching friction?



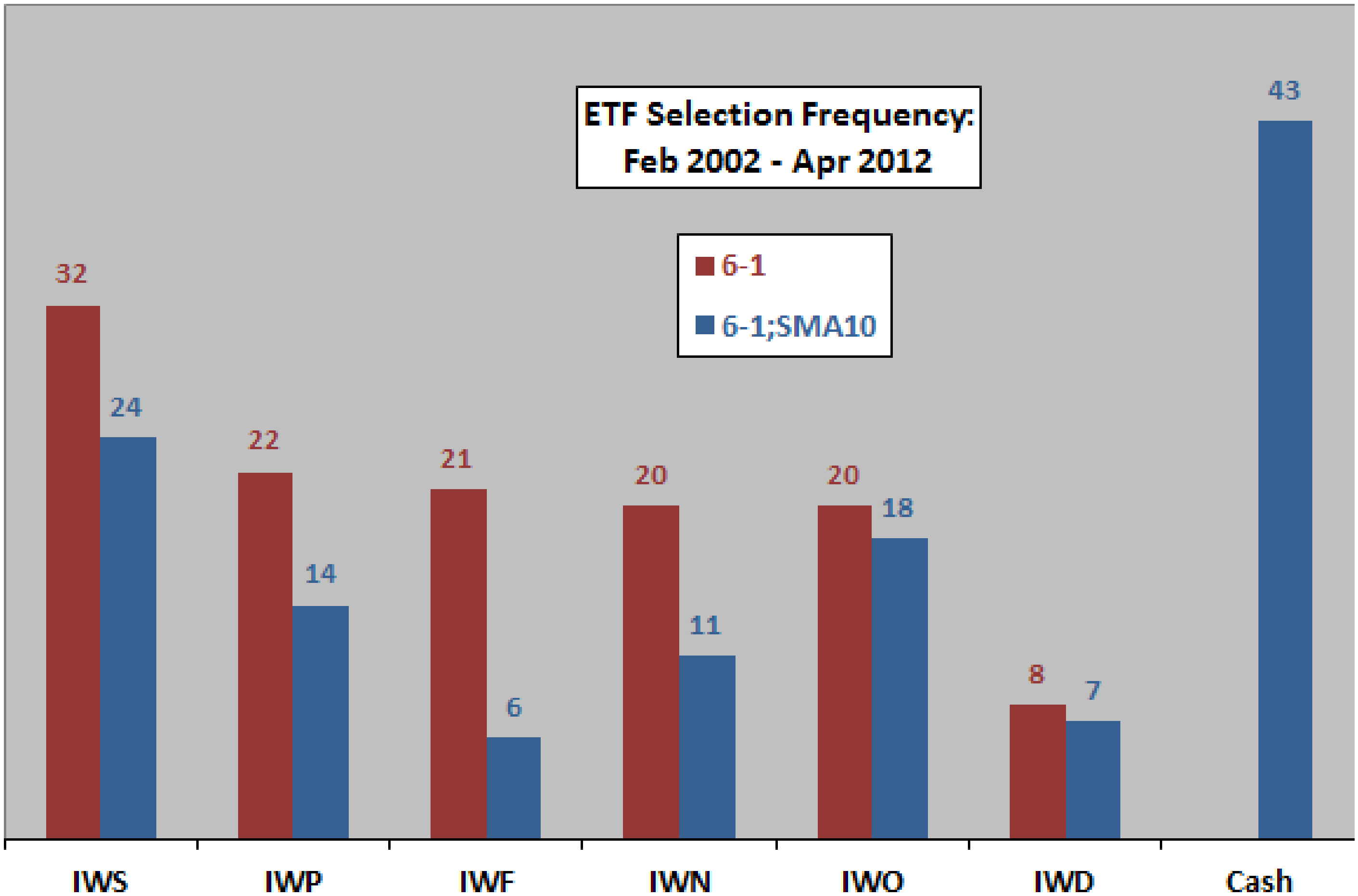
The next chart plots the terminal value of the 6-1 strategy for switching frictions ranging from 0.00% to 2.00%, along with the fixed terminal values of buying and holding SPY and holding the frictionless EW portfolio. Results indicate that the 6-1 strategy beats SPY at low, but achievable levels of switching friction. However, even a frictionless 6-1 strategy falls short of the EW portfolio benchmark.

How does the alternative 6-1;SMA10 strategy compare?



The next chart compares the distributions of style ETF winners/Cash for the 6-1 and 6-1;SMA10 strategies. The latter is in Cash for 43 of the 123 monthly winners (35%).

How does applying the 6-1;SMA10 strategy translate into cumulative returns?



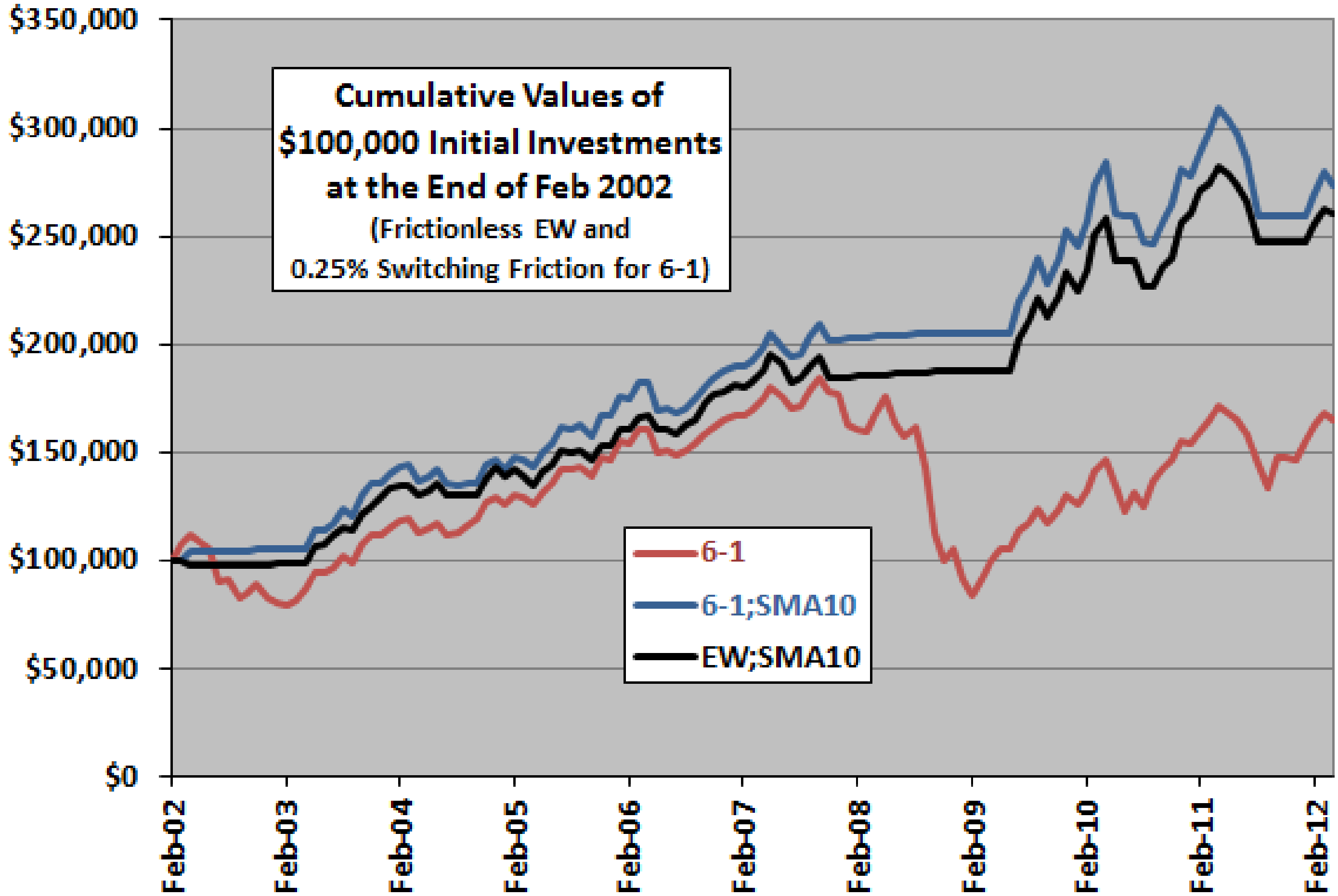
The next chart compares the cumulative values of $100,000 initial investments in the 6-1 strategy, the 6-1;SMA10 strategy and a benchmark EW:SMA10 strategy that holds the EW portfolio (goes to cash) when the S&P 500 Index is above (below) its 10-month simple moving average. As above, calculations derive from the following assumptions:

- Reallocate/rebalance at the close on the last trading day of each month (assume that values and total six-month past returns for the ETFs, and the S&P 500 Index 10-month simple moving average, can be calculated just before the close).
- Switching friction for the 6-1 and 6-1;SMA10 strategies is 0.25% of the balance whenever there is a change in holdings, but EW portfolio rebalancing is frictionless for conservative benchmarking.
- Ignore any tax implications of trading.

The 6-1;SMA10 strategy consistently outperforms the 6-1 strategy based on avoidance of most of major downturns. It also generally provides an edge over EW;SMA10, suggesting that style ETF momentum adds value to simple diversification during bull markets.

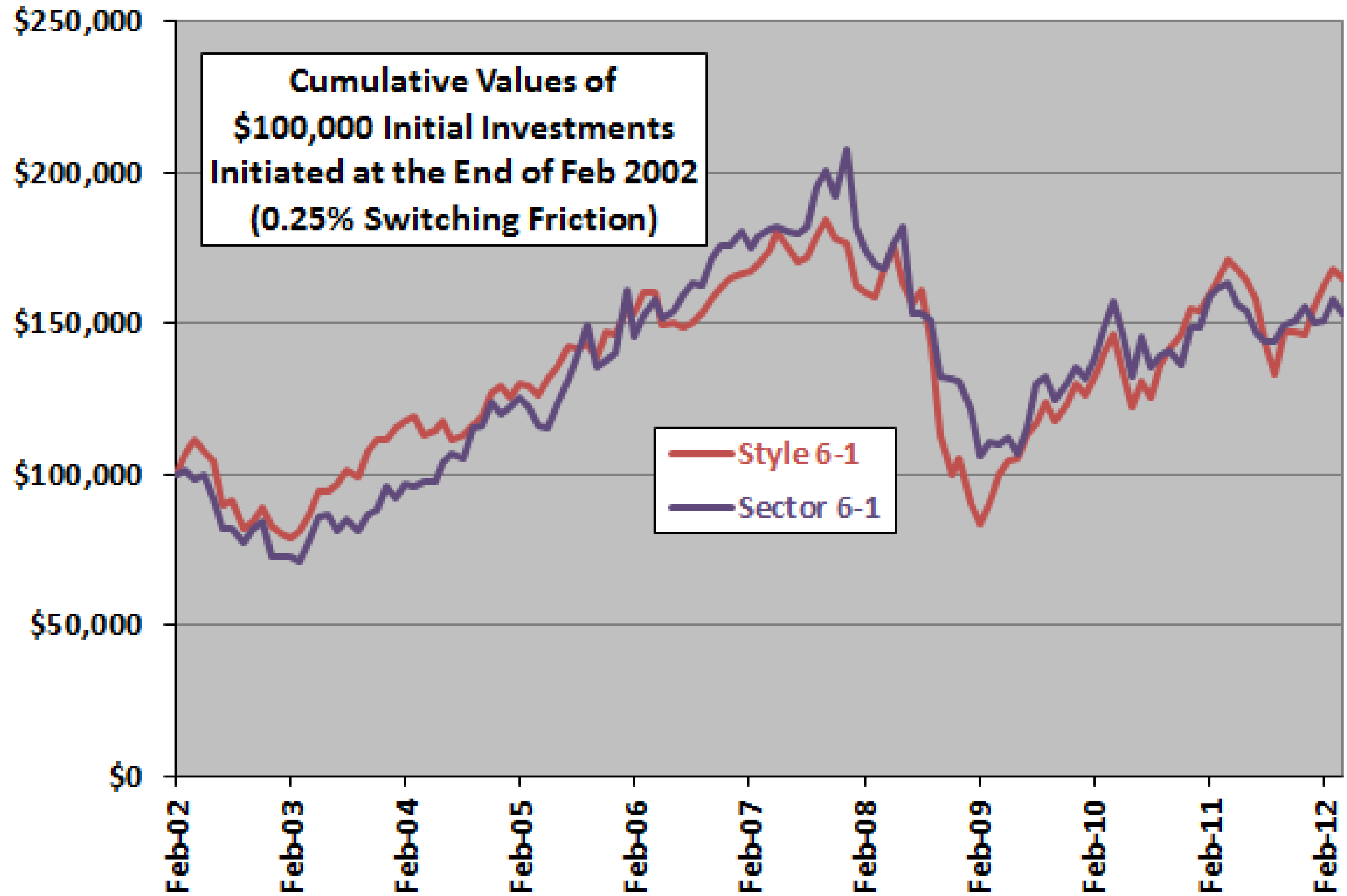
For reference, the average monthly gross return for the 6-1;SMA10 (6-1) strategy is 0.96% (0.64%), with standard deviation of monthly returns 3.14% (5.45%) and return-risk ratio 0.30 (0.12). Comparable statistics for EW;SMA10 are 0.83%, 2.90% and 0.29.

How does the simple style ETF momentum strategy fare against the "Simple Sector ETF Momentum Strategy", which switches among nine sector ETFs based on highest past six-month return?



The final chart compares cumulative values of $100,000 initial investments in the 6-1 style ETF momentum strategy and the 6-1 sector ETF momentum strategy over the available overlapping sample period (from the end of February 2002), with switching friction set at 0.25%. The performance of the two strategies is very similar.

The average monthly net return for the style (sector) ETF momentum strategy is 0.56% (0.51%, with standard deviation of monthly returns 5.46% (5.63%) and return-risk ratio 0.10 (0.09). The style (sector) strategy switches 38 (49) times, so decreasing trading friction favors the sector approach.



In summary, *evidence from a limited sample period suggests that a simple style ETF momentum strategy outperforms the overall stock market, but not a simple (equal-weighted) diversification approach or a simple sector ETF momentum strategy.*

For robustness tests, see "Doing Momentum with Style (ETFs) Robustness/Sensitivity Tests".

Cautions regarding findings include:

- Sample size is modest (about 21 independent six-month momentum ranking intervals and only about 13 independent 10-month intervals for SMA calculations).
- The selected ETF ranking interval derives from prior academic studies that most often use six-month and 12-month ranking intervals, with one-month holding intervals. This prior research may impound (and therefore transmit) data snooping bias, which is especially pernicious for small samples. Ranking intervals other than six months and holding periods other than one month may produce different results. Optimizing the ranking and holding intervals would elevate data snooping bias. Optimizing by considering different sets of trading vehicles also introduces data snooping bias.
- Including ETFs representing other asset classes (such as bonds, commodities, equity sectors and international stocks) may enhance results.
- Potential wildness in ETF monthly return distributions limits confidence in results.

Originally published at http://www.cxoadvisory.com/13330/size-effect/doing-momentum-with-style-etfs/ on May 8, 2012.

Hedges/Shorting to Exploit Sector ETF Momentum?

May 7, 2012

Readers have proposed several hedging/shorting variations for "Simple Sector ETF Momentum Strategy Performance", as follows: (1) buy the top and hedge with (short) the bottom sector based on past six-month return; (2) buy the top sector based on past six-month return and hedge it with a matched short position in the S&P 500 Index via ProShares Short S&P500 (SH); and, (3) buy the top (sell the bottom) sector when the S&P 500 Index is above (below) its 10-month simple moving average (SMA). The strategies apply to the following nine sector exchange-traded funds (ETF) defined by the Select Sector Standard & Poor's Depository Receipts (SPDR), all of which have trading data back to December 1998:

Materials Select Sector SPDR (XLB)
Energy Select Sector SPDR (XLE)
Financial Select Sector SPDR (XLF)
Industrial Select Sector SPDR (XLI)
Technology Select Sector SPDR (XLK)
Consumer Staples Select Sector SPDR (XLP)
Utilities Select Sector SPDR (XLU)
Health Care Select Sector SPDR (XLV)
Consumer Discretionary Select SPDR (XLY)

Using monthly dividend-adjusted closing levels for the sector ETFs, SPDR S&P 500 (SPY), SH (as available) and the 3-month Treasury bill (T-bill) yield over the period December 1998 through April 2012 (161 months), *we find that:*

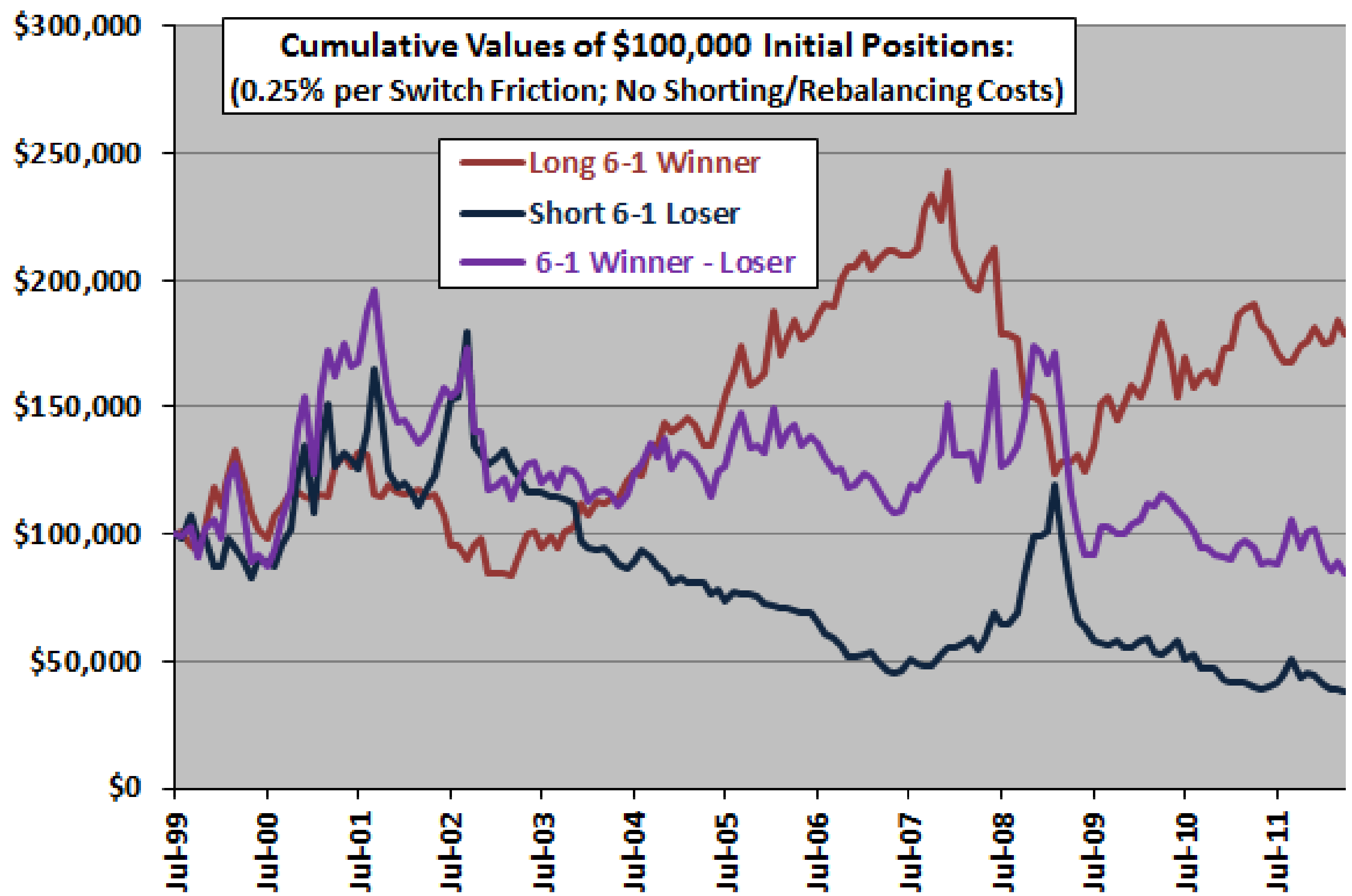
For all three hedging strategies, calculations assume the following:

- Reallocation occurs at the close on the last trading day of each month (accurate calculation of total six-month past ETF returns and the position of the S&P 500 Index relative to its 10-month SMA just before the close is feasible).
- Trading (switching) friction is 0.25% of the balance whenever there is a change in the ETF held or shorted.
- Ignore costs of shorting and any trading frictions for monthly rebalancing long and short sides.
- Return on cash for a benchmark strategy that goes to cash when the S&P 500 Index is below its 10-month SMA (6-1;SMA10) is equal to the T-bill yield at the time of allocation.
- Ignore effects of hedging on capital requirements.
- Ignore any tax implications of trading.

The following chart compares cumulative values of $100,000 initial investments that each month are long the sector ETF with the highest total return over the past six months (Long 6-1 Winner), short the sector ETF with the lowest (6-1 Loser) and the equally weighted combination (6-1; Winner-Loser) over the available sample period. The hedge strategy is limited in value because shorting the 6-1 loser is mostly unprofitable over the sample period. In fact, the sector ETF with the worst lagged six-month return is not the worst next-month performer among sector ETFs (see the first chart in "Simple Sector ETF Momentum Strategy Robustness/Sensitivity Tests"). Including costs of shorting the loser and trading frictions for rebalancing the long and short sides would lower hedge strategy performance (but proceeds from short positions would help fund the strategy, thereby reducing capital requirements).

For reference, the average monthly net return for the hedge strategy is 0.23%, with standard deviation of monthly returns 8.23%. For comparison the average monthly net return for the 6-1 winner (loser) is 0.54% (0.29%), with standard deviation 5.78% (7.94%). Hedging elevates rather than depresses volatility.

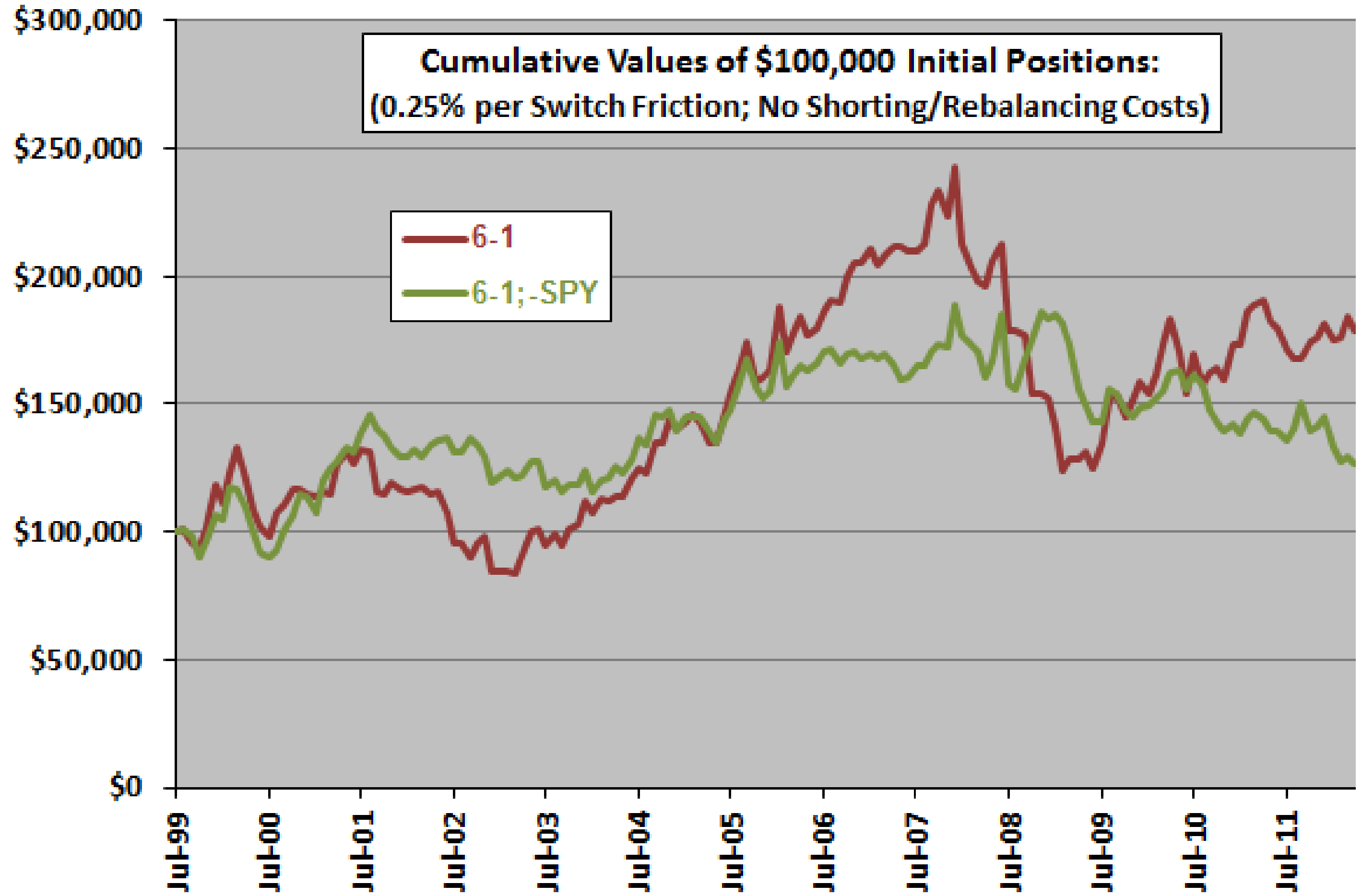
What about hedging by shorting SPY?



The next chart compares cumulative values of a $100,000 initial investment that each month is long the sector ETF with the highest total return over the past six months (6-1) and the combination of this basic strategy with a matched short position in SPY (6-1;-SPY) over the available sample period. Results indicate that the hedge strategy produces a somewhat inferior outcome at lower volatility. Costs of shorting and trading friction for monthly rebalancing the long and short sides would lower its performance (but proceeds from short position would help fund the strategy, thereby reducing capital requirements).

For reference, the average monthly net return of the 6-1 (6-1;-SPY) strategy over the sample period is 0.54% (0.28%), with standard deviation of monthly returns 5.78% (4.72%). Hedging does reduce volatility in this case.

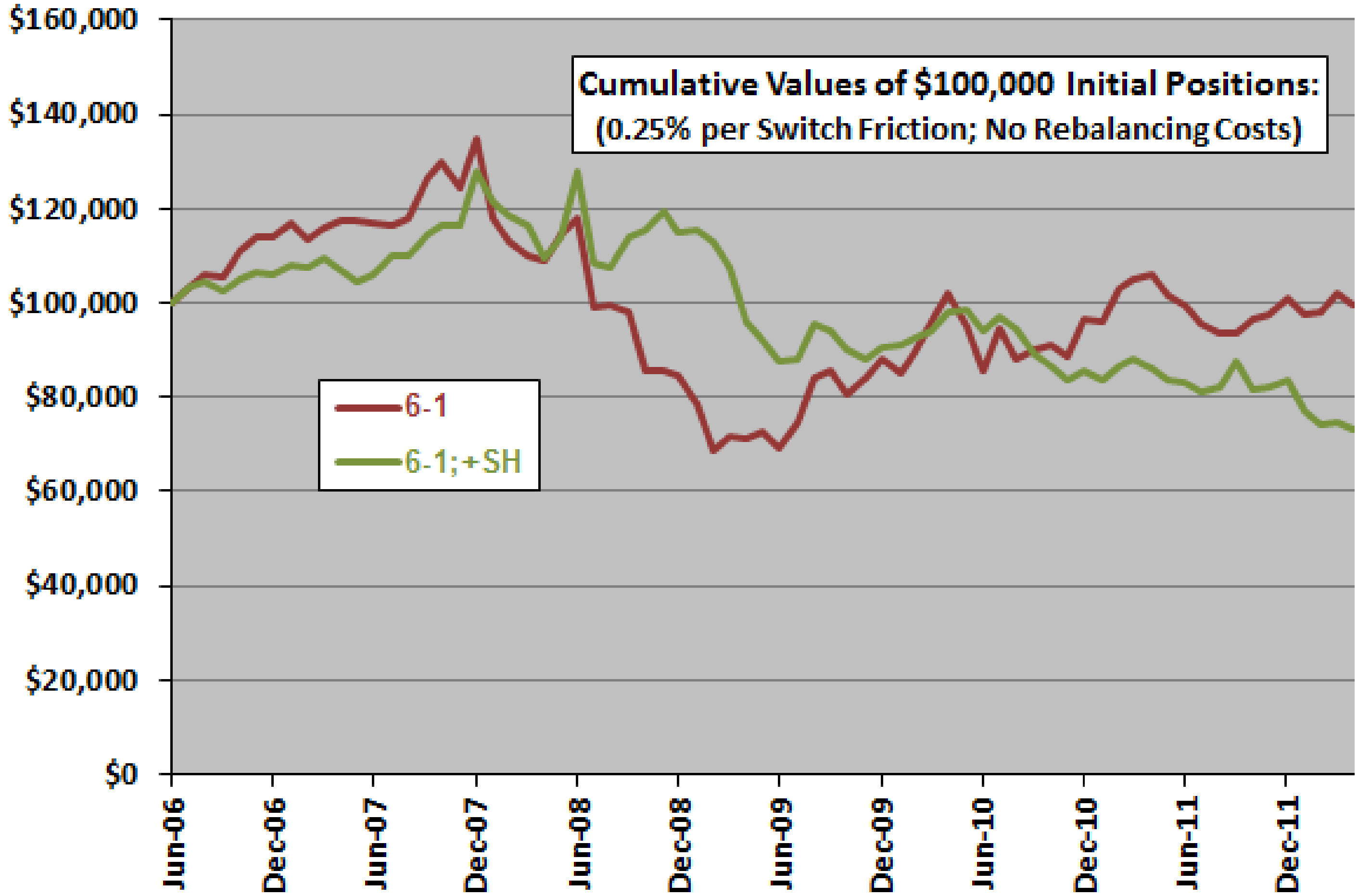
For a perhaps realistic view of shorting costs, we look at a long position in SH rather than a short in SPY.



The next chart compares the cumulative value of a $100,000 initial investment in the basic 6-1 momentum strategy and the combination of this basic strategy with a matched long position in SH (6-1;+SH) over the (much shorter) available sample period. Results indicate that neither the basic momentum strategy nor the the hedge strategy produce attractive outcomes. Trading friction for monthly rebalancing combination positions would lower hedging strategy performance. The available sample period is much too short for reliable inference.

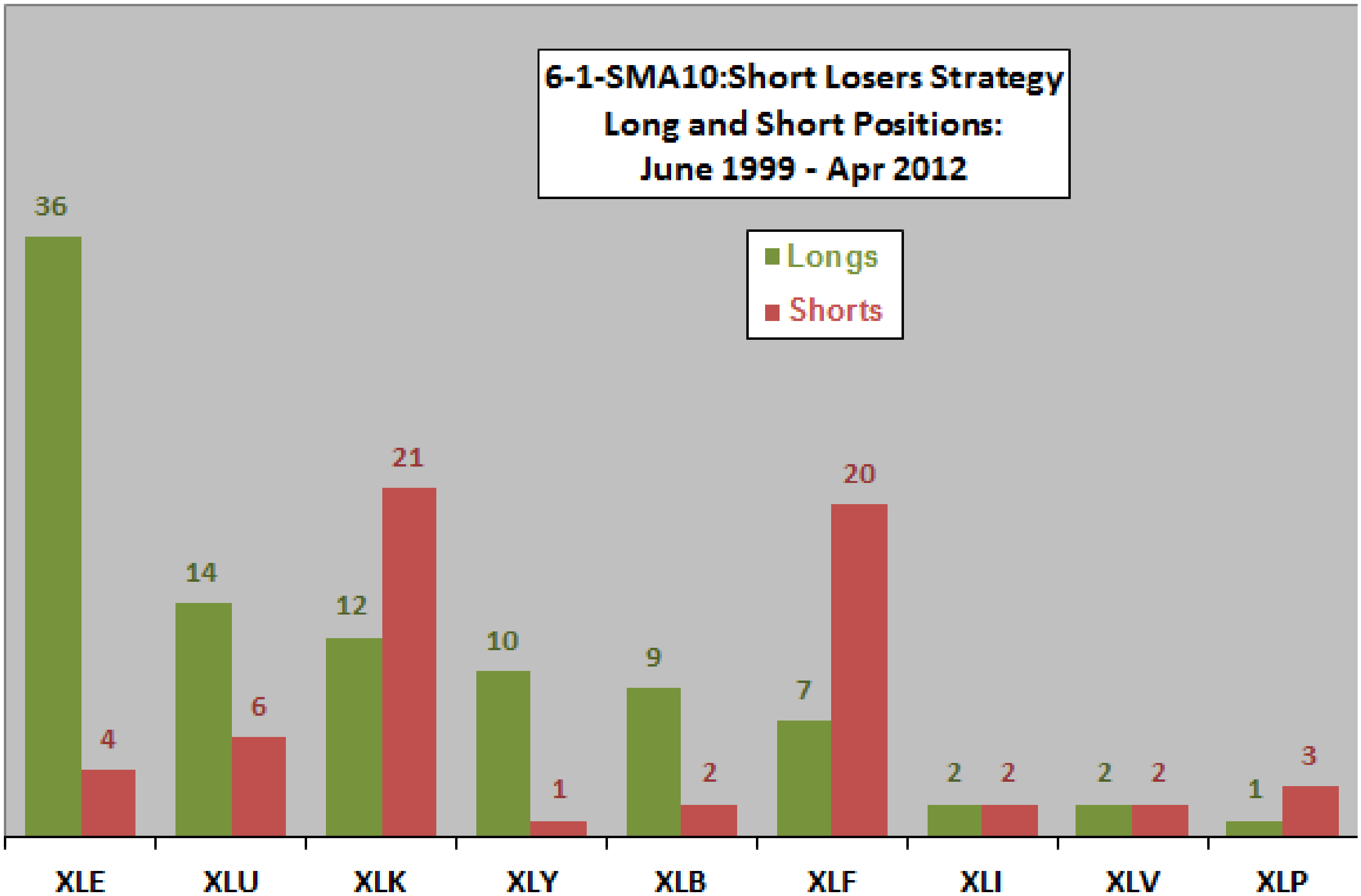
For reference, the average monthly net return of the 6-1 (6-1;+SH) strategy over the sample period is 0.15% (-0.35%), with standard deviation of monthly returns 5.50% (4.39%). Hedging does reduce volatility for this strategy.

Finally, we consider the more complex strategy involving the S&P 500 Index 10-month SMA.



The next chart shows the distribution of 93 long positions and 61 short positions for a strategy that is long (short) the sector ETF with the highest (lowest) total return over the past six months when the S&P 500 Index is above (below) its 10-month SMA (6-1;SMA10;Short Loser). The energy sector dominates the long positions, while the technology and financial sectors dominate the short positions.

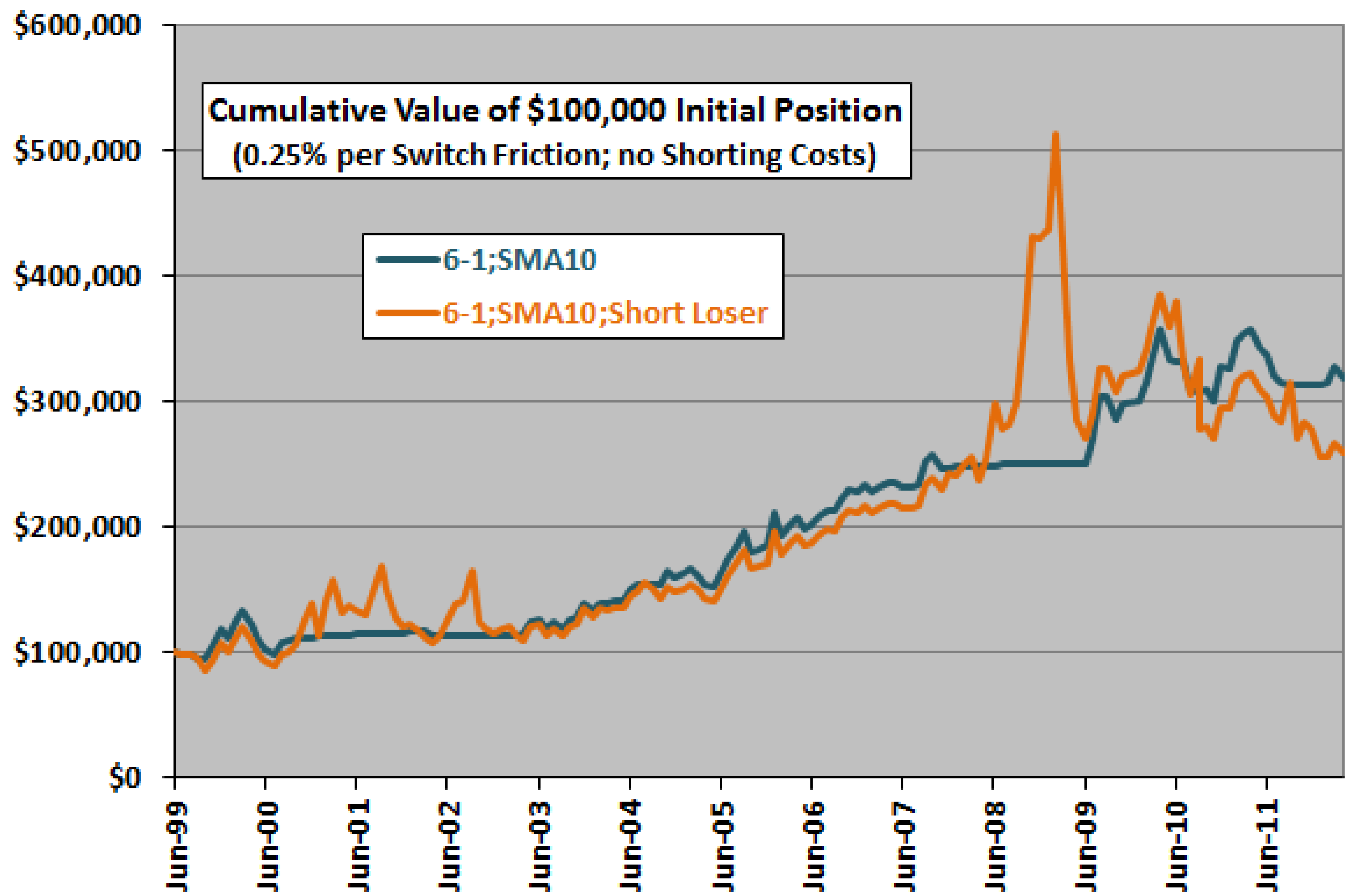
How does applying the 6-1;SMA10;Short Loser strategy translate into cumulative returns?



The next chart compares cumulative values of $100,000 initial investments in the 6-1;SMA10 benchmark strategy and the 6-1;SMA10;Short Loser strategy over the available sample period. The 6-1-SMA10 (6-1-SMA10:Short Loser) strategy switches 47 (63) times over the sample period. Unsurprisingly, the two strategies perform very similarly during bull markets and very differently during bear markets, but shorting momentum losers while the S&P 500 Index is below its 10-month SMA ("cash" conditions) may not yield a long-term advantage. Near the ends of bear markets, the strategy gives back gains from shorting early in bear markets.

Including costs for shorting would lower the performance of the 6-1-SMA10:Short Loser strategy during "cash" conditions.

How do the <u>monthly</u> return statistics for the two strategies compare during "cash" conditions?



The following table summarizes the average monthly net returns and the standard deviations of monthly net returns for the 6-1-SMA10 and 6-1-SMA10:Short Loser strategies during the 61 months the former is in cash. The 6-1-SMA10:Short Loser strategy has a higher average return but also a much higher volatility during these months. As shown above, the volatility works against the higher average in generating cumulative return. Including costs for shorting would lower the average monthly return of the 6-1-SMA10:Short Loser strategy.

S&P 500 Index Below 10-Month SMA	6-1;SMA10	6-1;SMA10; Short Loser
Average Monthly Return	0.12%	0.33%
Standard Deviation of Monthly Returns	0.16%	11.22%

In summary, *evidence from simple tests over available sample periods suggests that combining basic sector ETF momentum strategies with hedges/shorting does not generate compelling improvements in outcome.*

Cautions regarding findings include:

- Sample periods (especially for SH) are short in terms of number of independent six-month ranking intervals and 10-month SMA calculation intervals.

- Iterating tests on a given sample introduces data snooping bias (discovery of lucky indicators/parameter settings), thereby overstating results for the best performers. There may also be “second hand” data snooping bias derived from selecting indicators/ parameter settings based on findings of prior research using the same or similar data. Data snooping bias is especially pernicious for small samples.
- Potential wildness in ETF monthly return distributions limits confidence in results.

Originally published at http://www.cxoadvisory.com/3166/momentum-investing/a-hedge-strategy-to-exploit-sector-etf-momentum/ on May 7, 2012.

Alternative Sector ETF Momentum Metrics

May 7, 2012

Readers have suggested three alternative metrics for the strategy tested in the "Simple Sector ETF Momentum Strategy Performance": (1) Sharpe Ratio over the past six months; (2) slope of price over the past six months; and, (3) average of three-month, six-month and 12-month past returns. Do these metrics outperform past six-month return in a momentum strategy applied to the following nine sector exchange-traded funds (ETF) defined by the Select Sector Standard & Poor's Depository Receipts (SPDR), all of which have trading data back to December 1998:

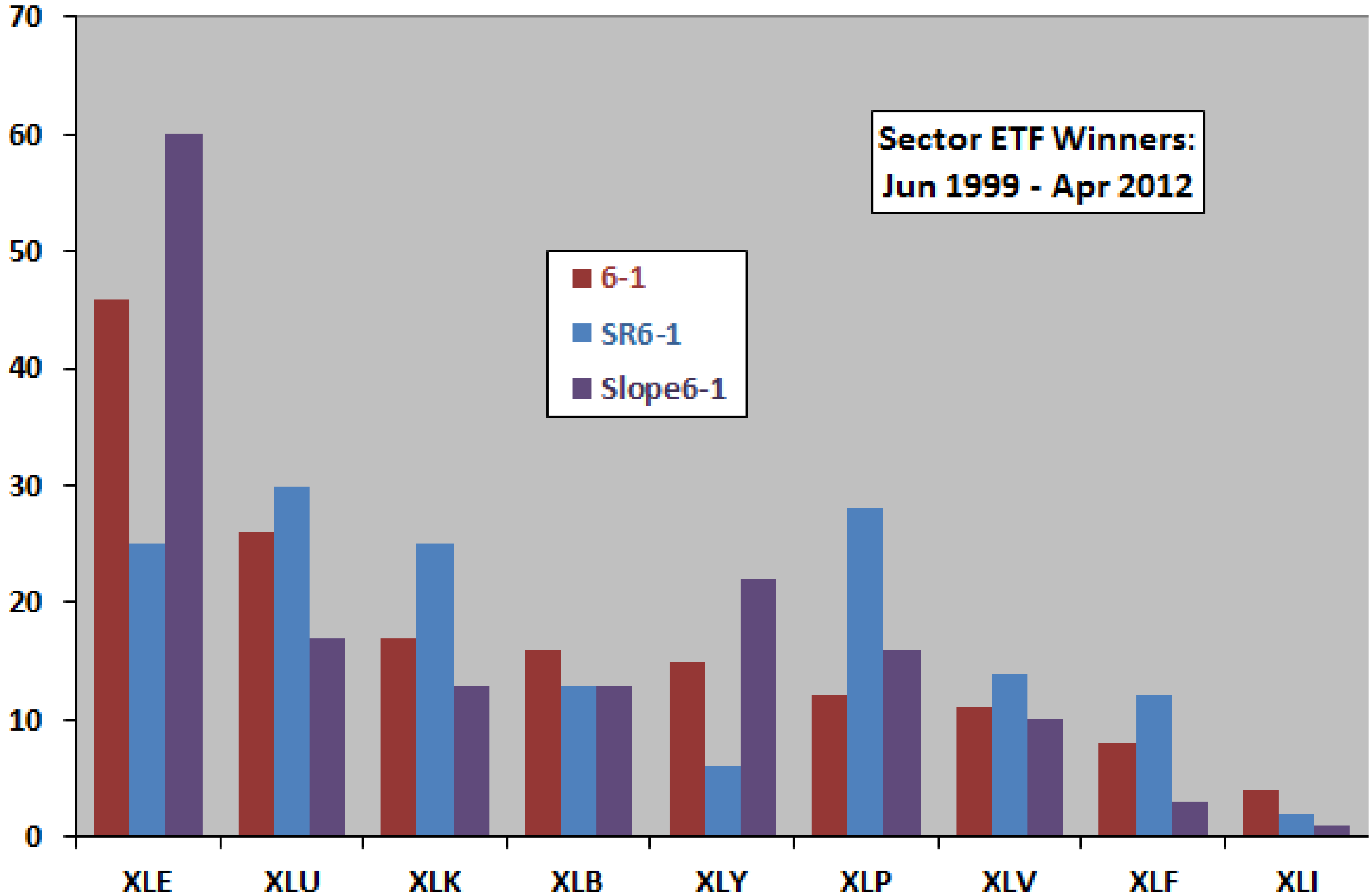
Materials Select Sector SPDR (XLB)
Energy Select Sector SPDR (XLE)
Financial Select Sector SPDR (XLF)
Industrial Select Sector SPDR (XLI)
Technology Select Sector SPDR (XLK)
Consumer Staples Select Sector SPDR (XLP)
Utilities Select Sector SPDR (XLU)
Health Care Select Sector SPDR (XLV)
Consumer Discretionary Select SPDR (XLY)

The three alternative strategies are, at the end of each month, allocate all funds to the sector ETF with the highest: (1) monthly Sharpe Ratio over the past six months (SR6-1); (2) monthly price slope over the past six months (Slope6-1); and, (3) average of past three-month, six-month and 12-month past total returns (3-1;6-1;12-1). For comparison, we include the strategy of monthly allocation to the sector ETF with the highest total return over the past six months (6-1). Using monthly dividend-adjusted closing prices for the nine sector ETFs over the period December 1998 through April 2012 (161 months), *we find that:*

We assume the risk-free rate is negligible (or unimportant) so that the SR6-1 signals derive from the mean monthly total return divided by the standard deviation of monthly total returns over the past six months. We examine the 3-1;6-1;12-1 alternative separately from the other two because of its shorter available test period.

The following chart compares the frequencies of sector ETF winners for the 6-1, SR6-1 and Slope6-1 strategies over the available sample period. The 6-1 strategy generates the most switches (62). The SR6-1 strategy tends to spread winners more evenly across ETFs.

How do cumulative returns of the three strategies compare?



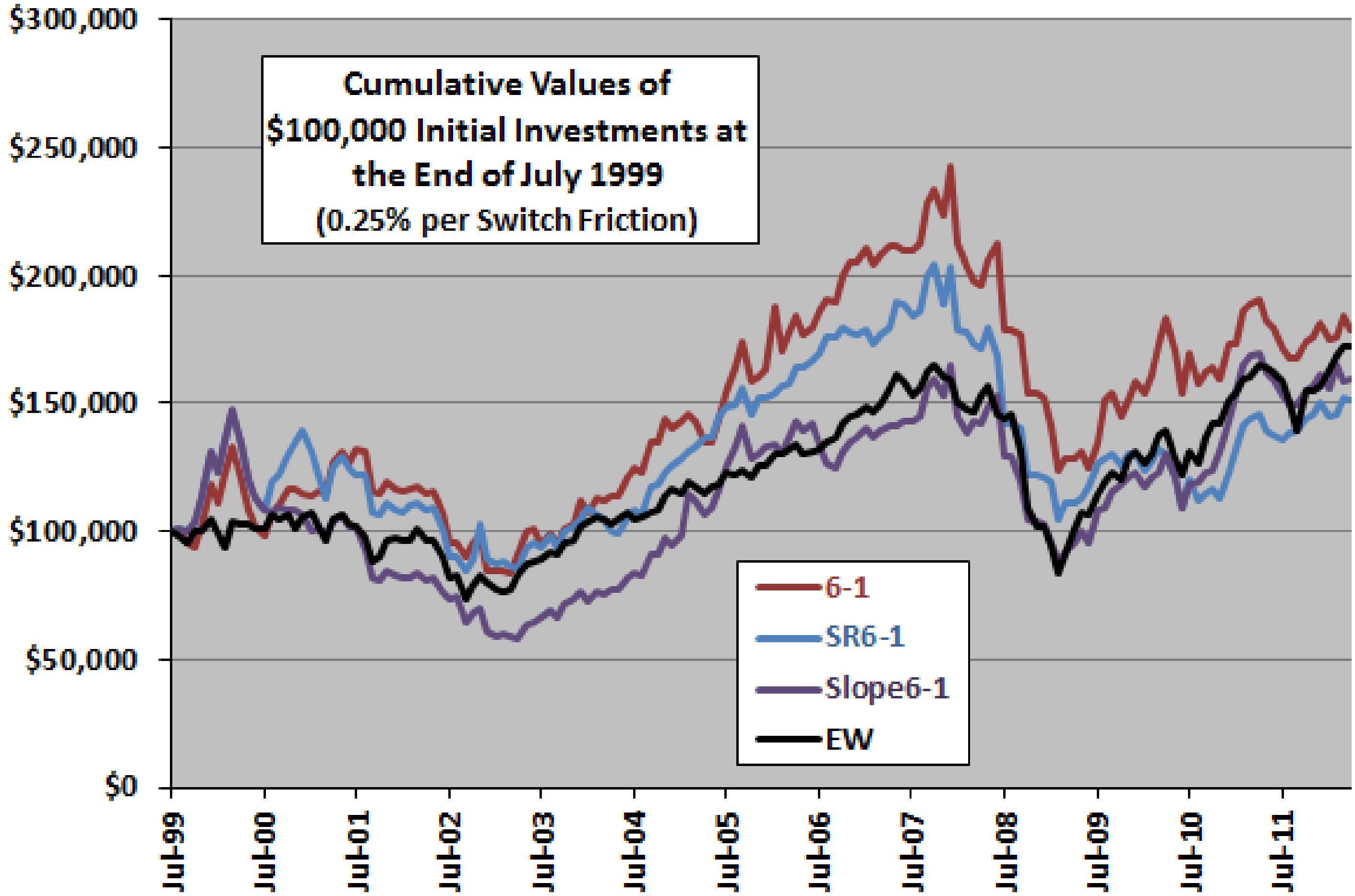
The next chart compares the cumulative values of $100,000 initial investments in the 6-1, SR6-1 and Slope6-1 strategies and in an equally weighted portfolio of the sector ETFs (EW), rebalanced monthly, over the available sample period. Calculations derive from the following assumptions:

- Reallocate at the close on the last trading day of each month (assume that we can calculate momentum metrics for the ETFs just before the close).
- Trading (switching) friction is 0.25% of the balance whenever there is a change in holdings, but EW portfolio rebalancing is frictionless for conservative benchmarking.

At the assumed level of switching friction, the original 6-1 strategy beats the SR6-1 and Slope6-1 strategies most of the time. Slope6-1 often underperforms EW.

The 6-1 strategy wins by a slightly wider margin with trading friction set to zero.

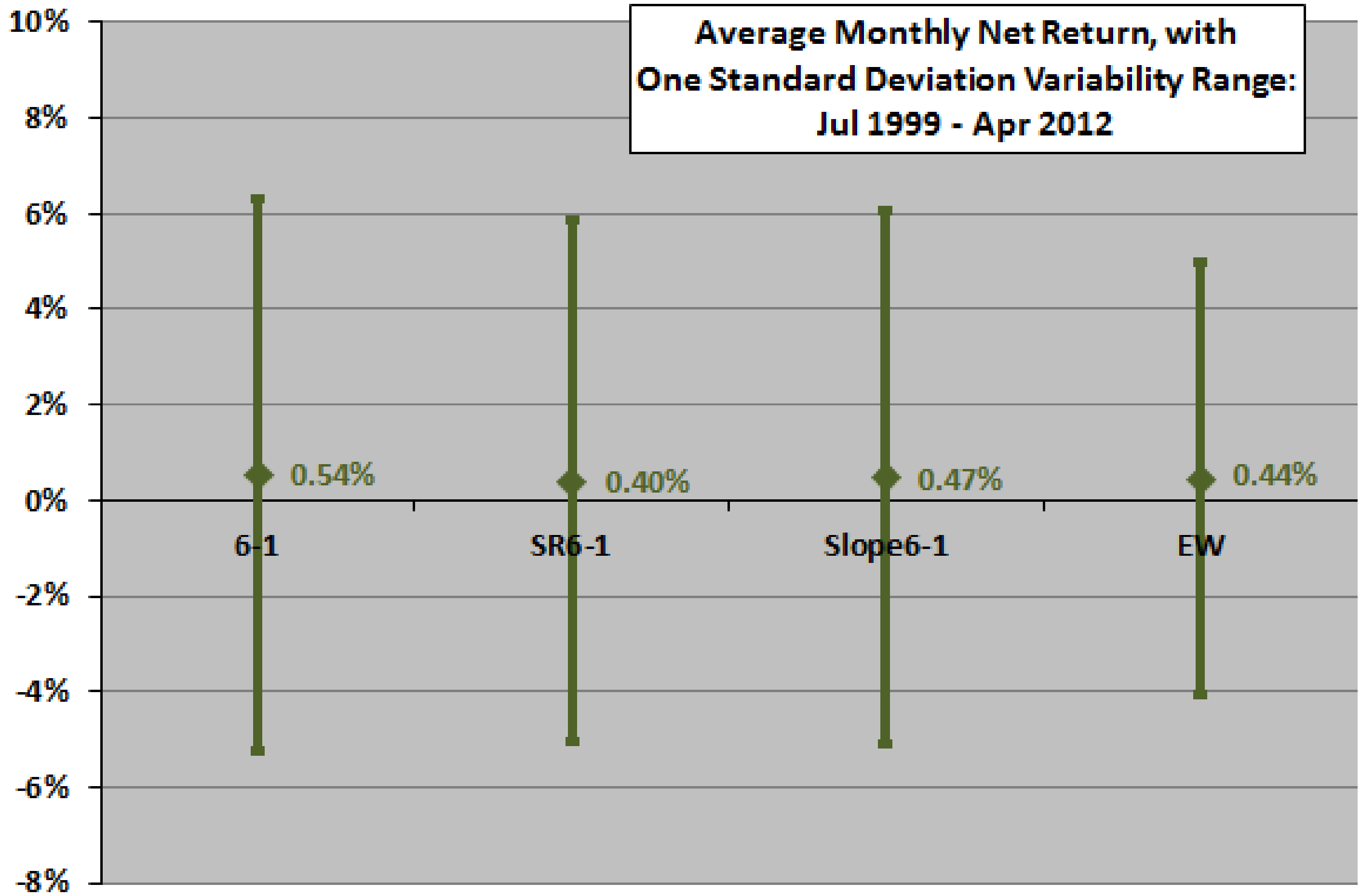
How do average monthly returns, as alternative measures of strategy performance, compare?



The next chart depicts the average monthly net total returns (with 0.25% switching frictions) and the standard deviations of monthly returns for the 6-1, SR6-1 and Slope6-1 strategies and EW over the available sample period. The three momentum strategies exhibit similar volatilities, with the 6-1 strategy having the highest average monthly return.

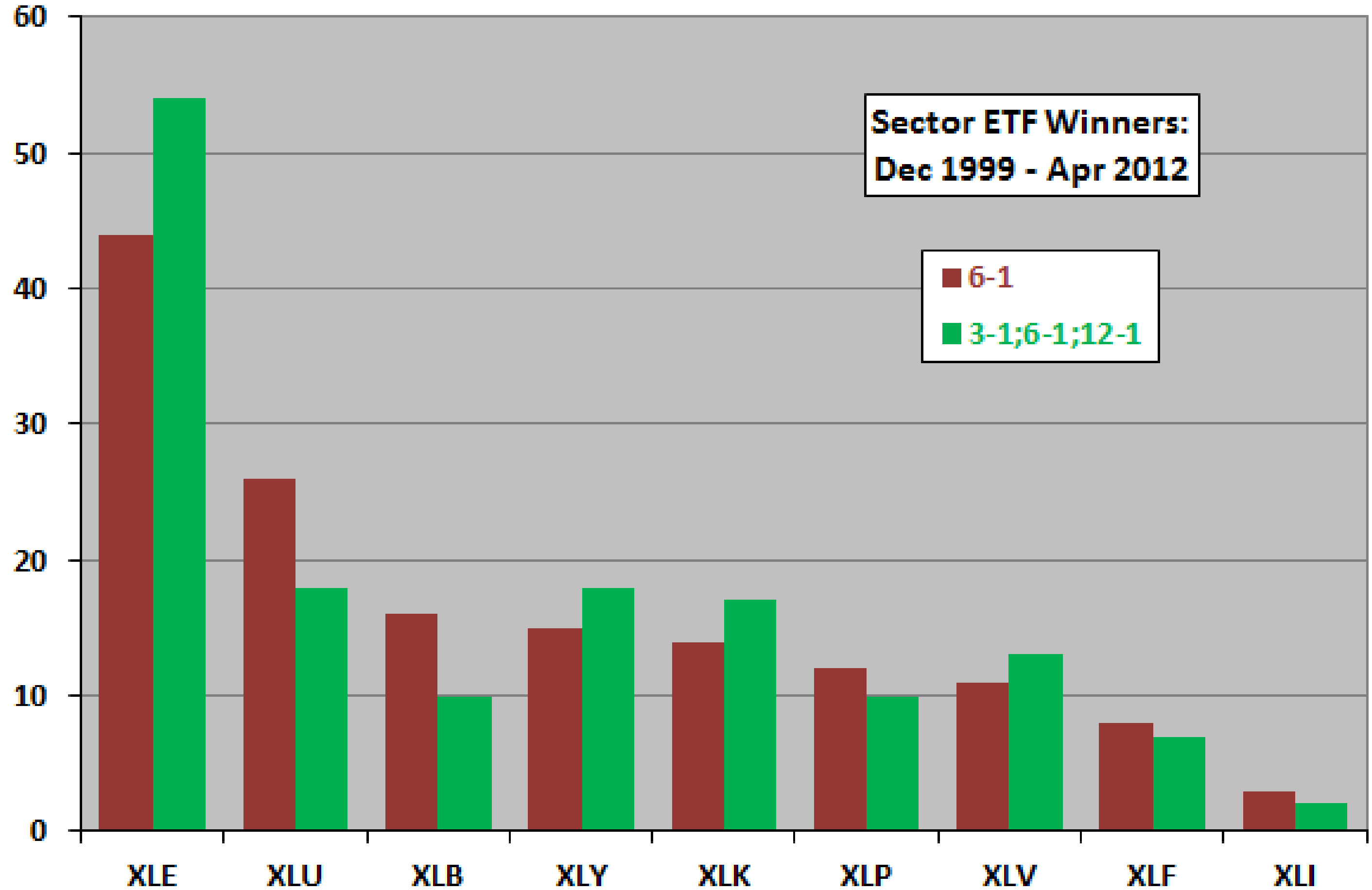
Setting trading friction to zero improves average monthly returns by 0.08%-0.10% for the three alternatives.

What about the 3-1;6-1;12-1 strategy?



The next chart compares the frequencies of sector ETF winners for the 6-1 and 3-1:6-1:12-1 strategies over the available sample period. Because of its construction, the test period for the 3-1;6-1;12-1 strategy begins in January 2000 rather than July 1999 (to allow calculation of 12-month lagged returns). The 3-1:6-1:12-1 strategy is a little less diversified across ETFs over time and generates fewer switches (49 versus 59).

How do cumulative returns of the two strategies compare?

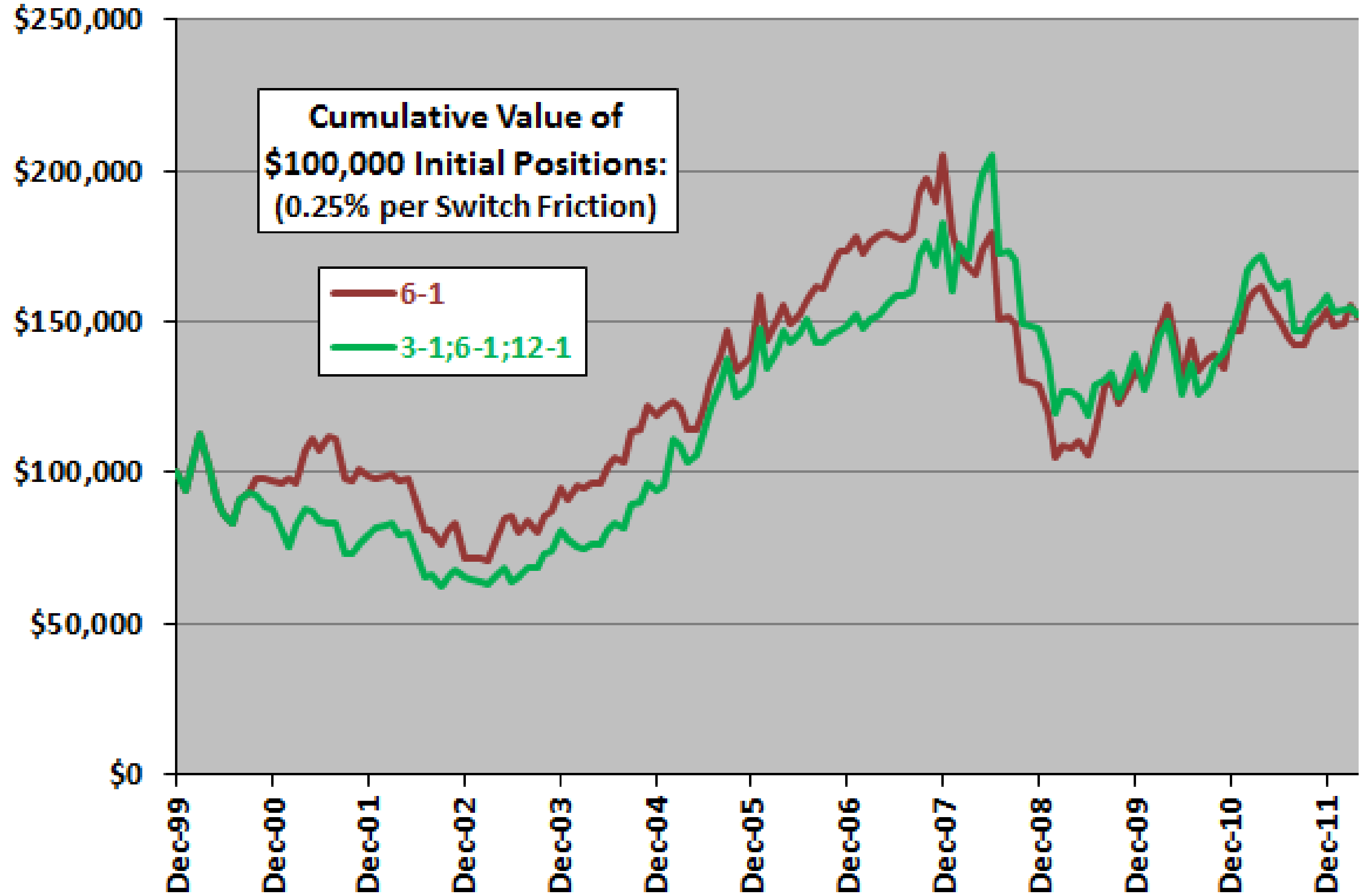


The next chart compares the cumulative values of $100,000 initial investments in the 6-1 and 3-1:6-1:12-1 strategies over the available sample period. Calculations derive from the same assumptions used above (with 0.25% switching frictions).

The 3-1:6-1:12-1 strategy trails the 6-1 strategy over most of the sample period (until the 2008-2009 financial crisis). Note that the second chart in “Simple Sector ETF Momentum Strategy Robustness/Sensitivity Tests” suggests 3-month (12-month) lagged returns perform poorly (indifferently) as standalone selectors of momentum winners over the sample period.

Setting trading friction to zero slightly degrades the performance of the 3-1;6-1;12-1 strategy relative to the 6-1 strategy.

The average monthly net total return for the 6-1 (3-1:6-1:12-1) strategy with 0.25% switching friction is 0.44% (0.46%) over the entire sample period, with standard deviation of monthly returns 5.69% (5.82%).



In summary, *evidence from simple tests does not support a belief that any of the three alternative momentum metrics reliably beat past six-month return for a sector ETF momentum strategy, but averaging returns over the past three, six and 12 months may be just as good.*

Cautions regarding findings include:

- Sample size is modest (just 27 independent six-month momentum ranking intervals and 13 independent 12-month ranking intervals).
- Iterating tests on a given sample introduces data snooping bias (discovery of lucky indicators/parameter settings), thereby overstating results for the best performer. There may also be "second hand" data snooping bias derived from selecting indicators/ parameter settings based on findings of prior research using the same or similar data. Data snooping bias is especially pernicious for small samples.
- Potential wildness in ETF monthly return distributions limits confidence in results.

Originally published at http://www.cxoadvisory.com/4498/momentum-investing/alternative-sector-etf-momentum-metrics/ on May 7, 2012.

Simple Sector ETF Momentum Strategy Robustness/ Sensitivity Tests

May 7, 2012

How sensitive is the performance of the "Simple Sector ETF Momentum Strategy" to selecting ranks other than winners and to choosing a momentum ranking interval other than six months? This strategy each month ranks the following nine sector exchange-traded funds (ETF) on past return and rotates to the strongest sector:

Materials Select Sector SPDR (XLB)
Energy Select Sector SPDR (XLE)
Financial Select Sector SPDR (XLF)
Industrial Select Sector SPDR (XLI)
Technology Select Sector SPDR (XLK)
Consumer Staples Select Sector SPDR (XLP)
Utilities Select Sector SPDR (XLU)
Health Care Select Sector SPDR (XLV)
Consumer Discretionary Select SPDR (XLY)

Available data are so limited that sensitivity test results may mislead. With that reservation, we perform two robustness/sensitivity tests: (1) comparison of returns for all nine ranks of winner through loser based on a ranking interval of six months and a holding interval of one month (6-1); and, (2) comparison of winner returns for ranking intervals ranging from one to 12 months (1-1 through 12-1) and for a six-month lagged six-month ranking interval (12:7-1) per "Isolating the Decisive Momentum (Echo?)", all with one-month holding intervals. Using monthly adjusted closing prices for the sector ETFs and SPDR S&P 500 (SPY) over the period December 1998 through April 2012 (161 months), *we find that:*

All calculations assume that monthly reallocation/rebalancing occurs at the close on the last trading day of each month (assuming that past returns for the ETFs can be calculated for ranking purposes just before the close).

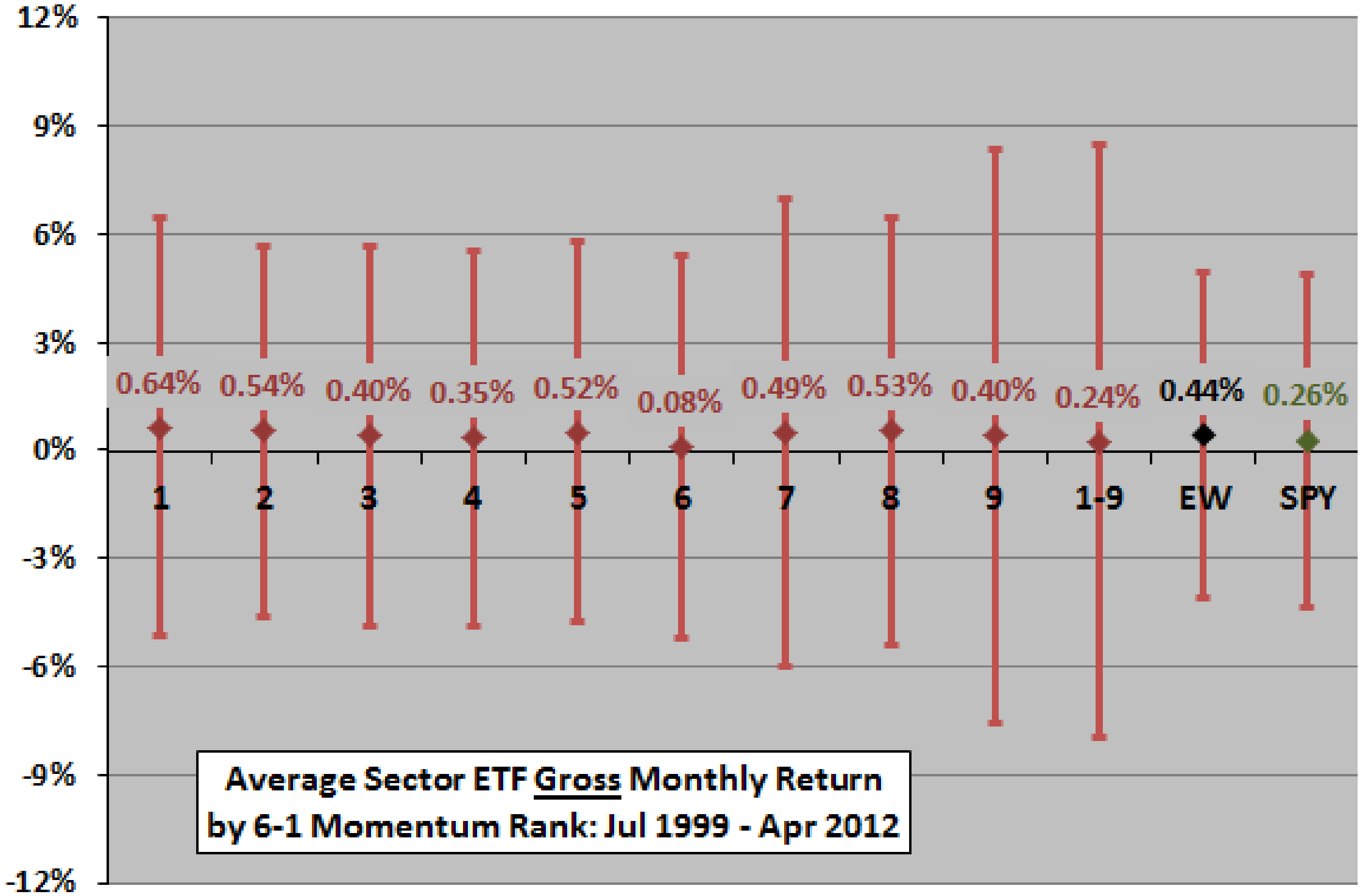
The following chart shows average monthly 6-1 sector momentum strategy gross returns for rank 1 (highest momentum) through rank 9 (lowest momentum) since July 1999, with one standard deviation variability ranges. The chart also shows comparable statistics for an equally weighted, monthly rebalanced (EW) portfolio of the nine sectors as a simple benchmark (representing the value of diversification) and for SPY. Notable points are:

- Ranks 1 and 2 have the highest average returns, and the difference in average returns

between ranks 1 and 9 is positive.
- Average returns do not decline systematically from rank 1 through rank 9. Rank 6 has the lowest average return, and returns for ranks 7 and 8 are higher than those for ranks 3 and 4.

Results do not compelling support belief in sector momentum strategy reliability.

What happens for ranking intervals other than six months?

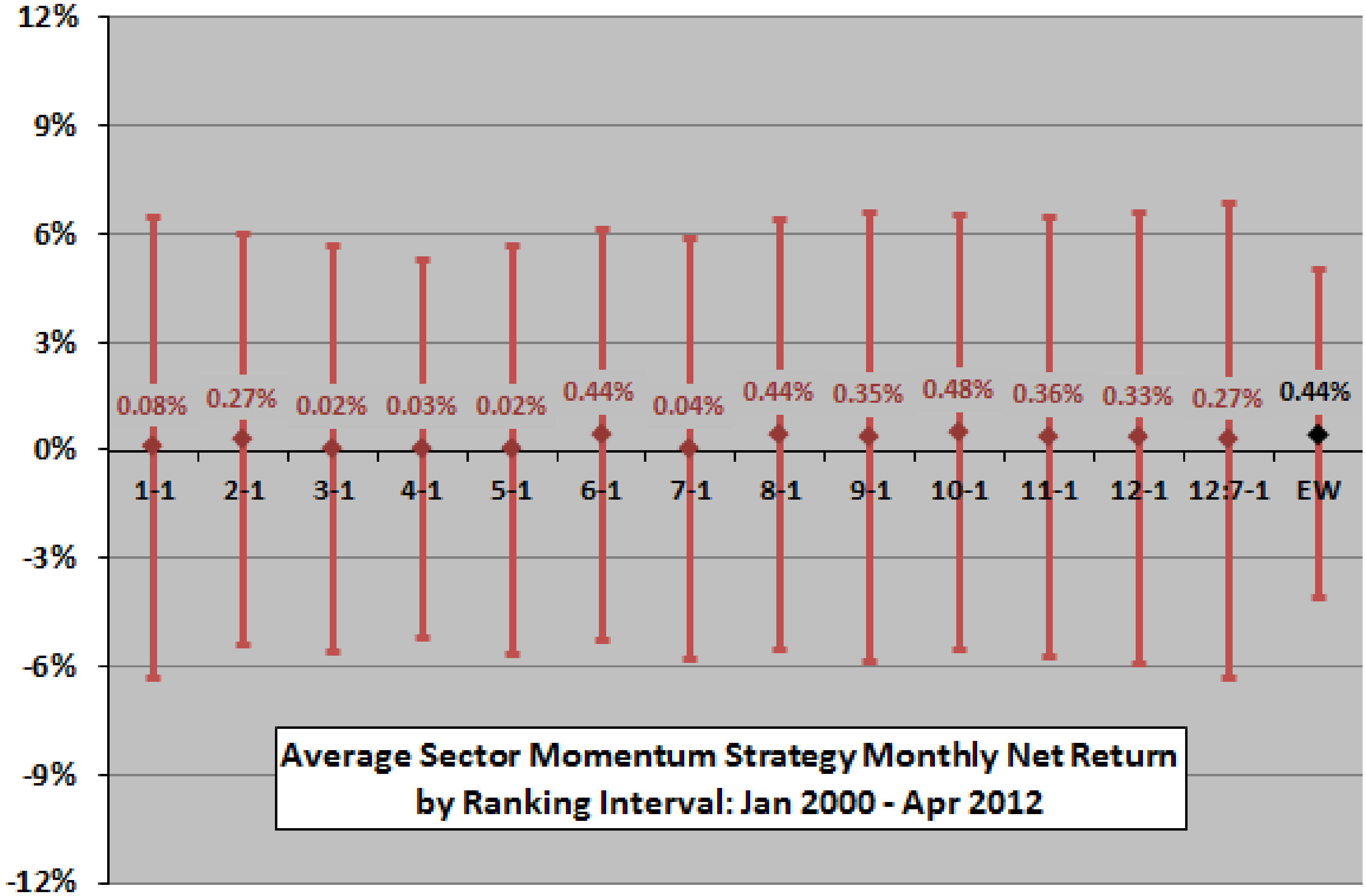


The next chart shows average monthly net returns for sector momentum strategies 1-1 through 12-1 and 12:7-1 since January 2000 (allowing a 12-month return calculation). The assumed level of trading (switching) friction is 0.25% of the balance for all ranking intervals. Monthly EW portfolio rebalancing is frictionless for conservative benchmarking. Results suggest that:

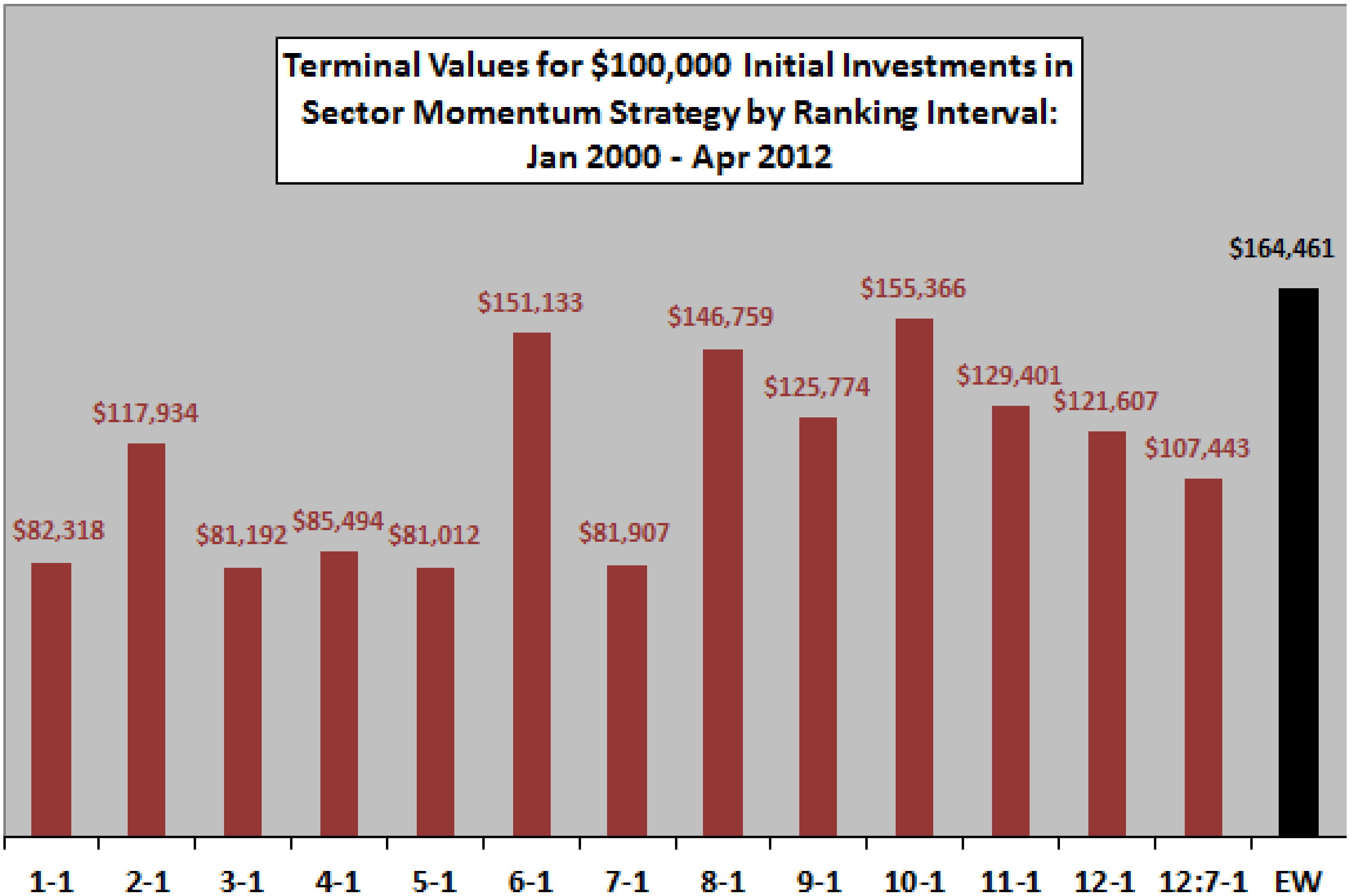
- Ranking intervals of six, eight and ten months best fit U.S. equity sectors over the available sample period. Perhaps widespread use of six-month and 10-month ranking intervals is germane.
- While longer ranking intervals generally outperform short ones, the seven-month interval and the 12:7-1 alternative do not work well.
- Variation across ranking intervals is not systematic, undermining belief in a stable best choice.

The available sample period is very short for confident inference. The best ranking intervals may be lucky rather than fundamentally meaningful.

For another perspective, we look at terminal values of equal investments across ranking intervals.



The final chart summarizes terminal values of $100,000 initial investments for sector momentum strategies 1-1 through 12-1 and 12:7-1 since December 1999. Results generally confirm that ranking intervals of six, eight and ten months work best over the sample period. However, these choices do not beat the frictionless EW portfolio, which is much less volatile. At the assumed level of trading friction, five ranking intervals lose money.



In summary, *evidence from momentum rank and ranking interval sensitivity tests for a limited sample offer little support for belief in simple sector ETF momentum strategy reliability. In the available sample, selecting the top rank based on a ranking interval of six months is among the best alternatives.*

Results suggest that it is important to add a rule to avoid bear markets, such as the 10-month simple moving average signal described in "Simple Sector ETF Momentum Strategy".

Cautions regarding findings include:

- The performance of the best (worst) ranking/ranking interval incorporates data snooping bias and therefore likely overstates (understates) expected performance.
- As noted, sample sizes (only 27 independent six-month ranking intervals in the first test and 13 independent 12-month ranking intervals in the second test) are very small for confident inference.
- The method/parameters derive from research on individual stocks. While arguable that the findings should carry over to ETFs, there might be confounding effects. For example, hedging practices (using a sector ETF to hedge positions in individual stocks from the sector) might affect translation of an anomaly from individual stocks to ETFs.
- To the extent return distributions are wild rather than normal, average returns and standard deviations of returns lose meaning as estimators of future returns.

Originally published at http://www.cxoadvisory.com/4474/momentum-investing/simple-sector-etf-momentum-strategy-robustnesssensitivity-tests/ on May 7, 2012.

Simple Sector ETF Momentum Strategy

May 7, 2012

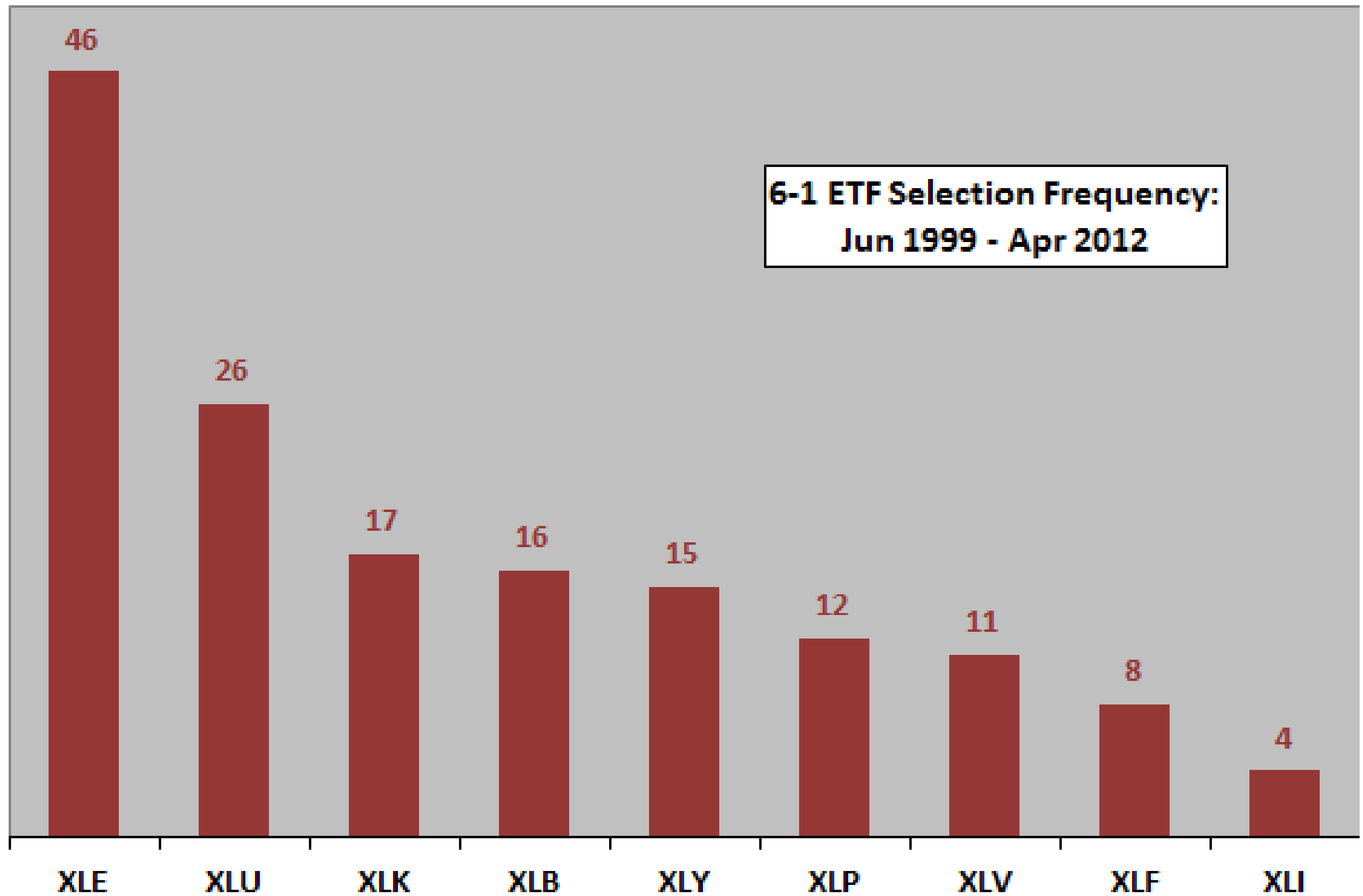
Do simple momentum trading strategies applied to major U.S. stock market sectors outperform reasonable benchmarks? To investigate, we apply three simple momentum strategies to the nine sector exchange-traded funds (ETF) defined by the Select Sector Standard & Poor's Depository Receipts (SPDR):

Materials Select Sector SPDR (XLB)
Energy Select Sector SPDR (XLE)
Financial Select Sector SPDR (XLF)
Industrial Select Sector SPDR (XLI)
Technology Select Sector SPDR (XLK)
Consumer Staples Select Sector SPDR (XLP)
Utilities Select Sector SPDR (XLU)
Health Care Select Sector SPDR (XLV)
Consumer Discretionary Select SPDR (XLY)

The three strategies are: (1) allocate all funds at the end of each month to the sector ETF with the highest total return over the past six months (6-1); (2) allocate all funds at the end of each month to the sector ETF with the highest total return over the six months ending the prior month (6-1;1), hypothesizing that the skip-month avoids short-term reversals; and, (3) more cautiously, allocate all funds at the end of each month either to the sector ETF with the highest total return over the past six months or to cash depending on whether the S&P 500 Index is above or below its 10-month simple moving average (6-1;SMA10). A six-month ranking period is intuitively large enough to gauge sector momentum but small enough to react to changes in business conditions that might favor one sector over others. Using monthly adjusted closing prices for the sector ETFs, the S&P 500 index, 3-month Treasury bills (T-bills) and S&P Depository Receipts (SPY) over the period December 1998 through April 2012 (161 months), *we find that:*

The following chart shows the distribution of sector ETF winners based on past six-month total return over the entire sample period. The energy sector comprises 46 of the 155 monthly winners (30%).

How does applying the above 6-1 and 6-1;1 strategies translate into cumulative returns?

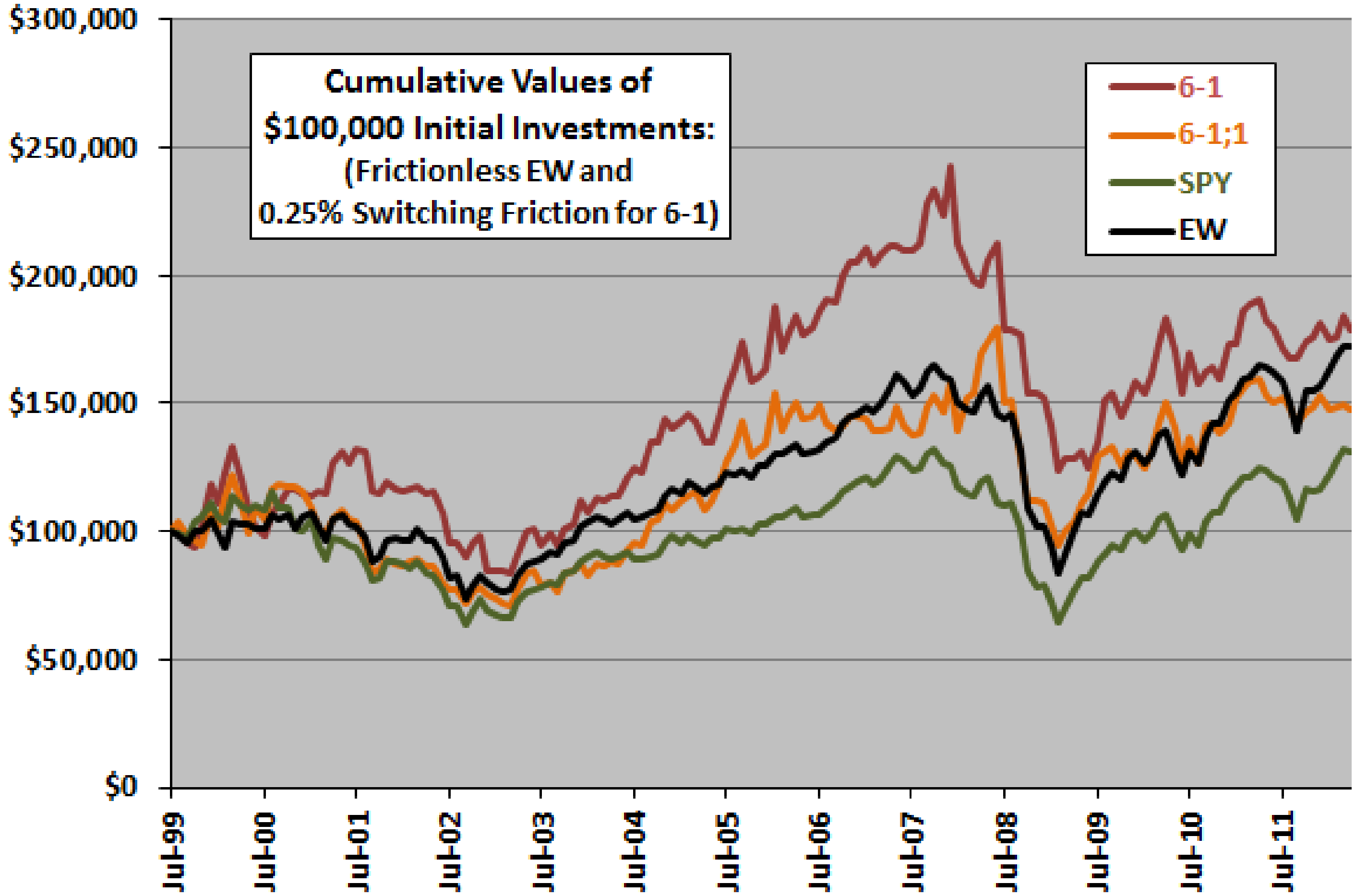


The next chart compares the cumulative values of $100,000 initial investments in the 6-1 and 6-1;1 strategies, SPY and an equally weighted portfolio of the sector ETFs (EW), rebalanced monthly, over the available sample period. Calculations derive from the following assumptions:

- Reallocate/rebalance at the close on the last trading day of each month (assume that values and total six-month past returns for the ETFs can be calculated just before the close).
- Trading (switching) friction for the 6-1 and 6-1;1 strategies is 0.25% of the balance whenever there is a change in holdings, but EW portfolio rebalancing is frictionless for conservative benchmarking.
- Ignore any tax implications of trading.

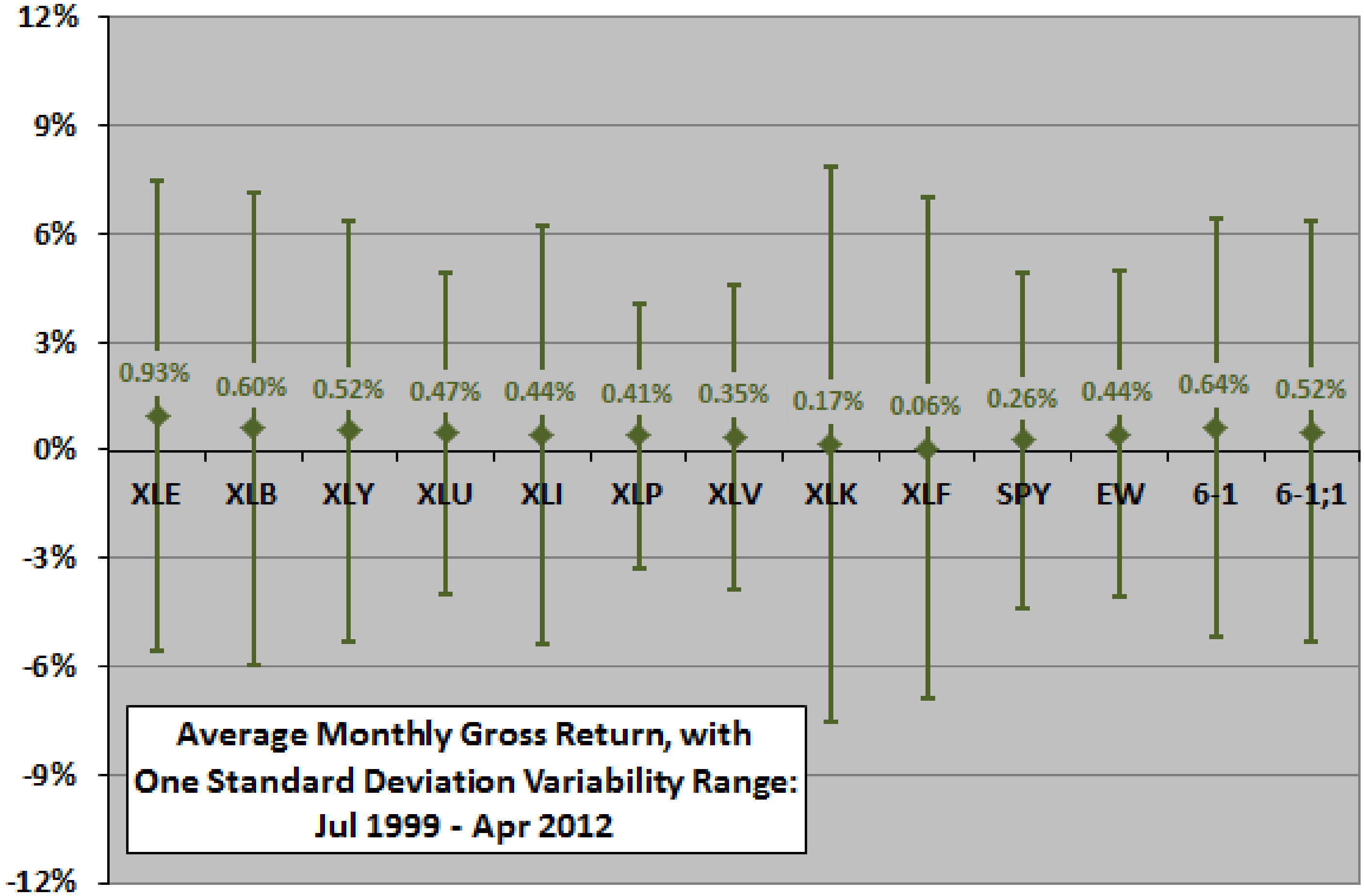
At the assumed level of switching friction, the 6-1 strategy generally outperforms both SPY and the EW portfolio, adding value to simple diversification. The 6-1;1 strategy approximately matches the EW portfolio, unsupportive of a belief that a skip-month avoids any short-term reversals at the sector level.

How do average monthly returns, as alternative measures of strategy performance, compare?



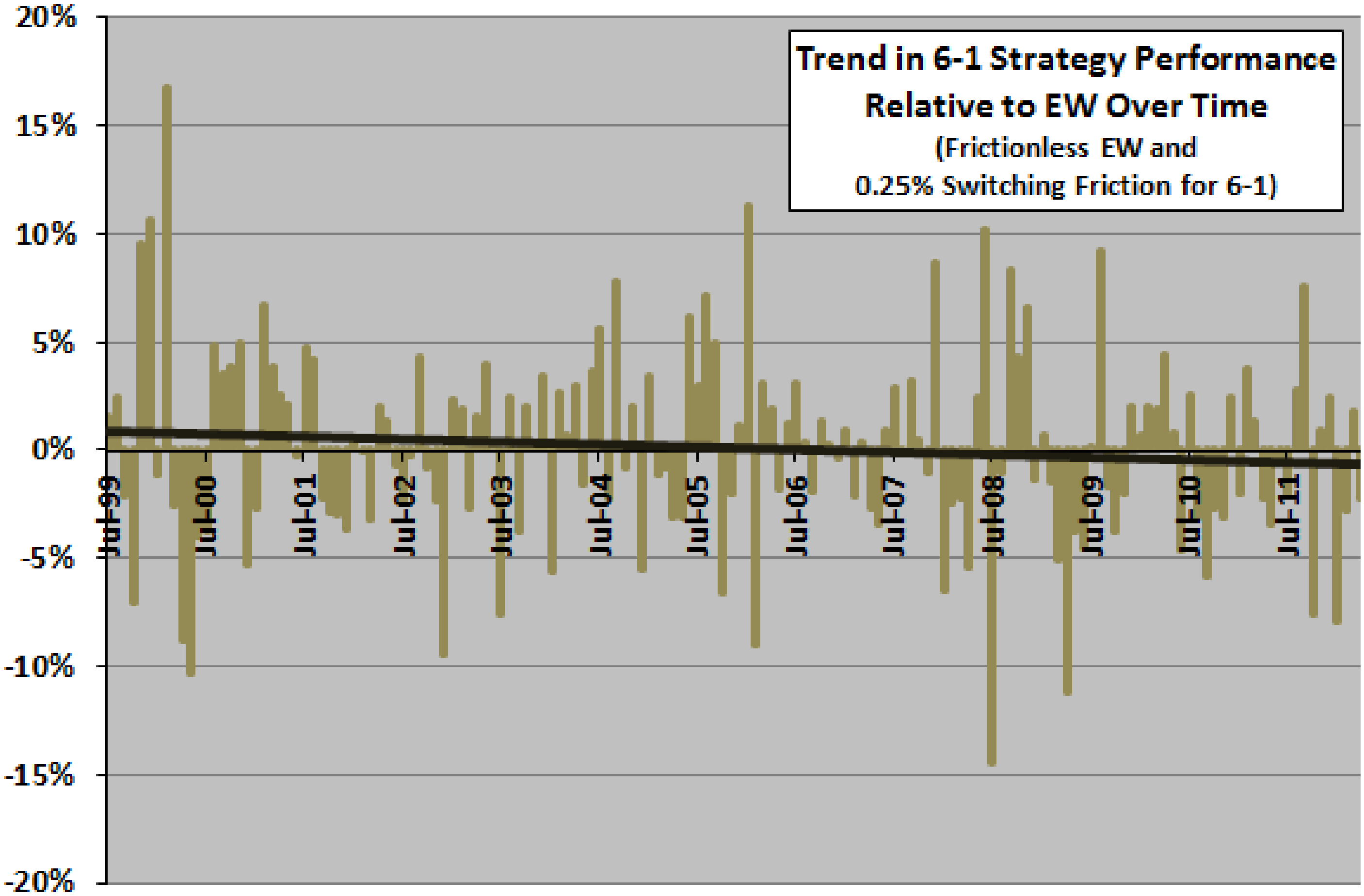
The next chart summarizes gross average (arithmetic mean) monthly returns and standard deviations of monthly returns for each of the sector ETFs, SPY, the EW portfolio and the 6-1 and 6-1;1 strategies over the available sample period. The 6-1 strategy, while generating a higher gross average monthly return than the EW portfolio, is considerably more volatile.

Is the performance of the 6-1 style strategy relative to the EW portfolio stable over time?



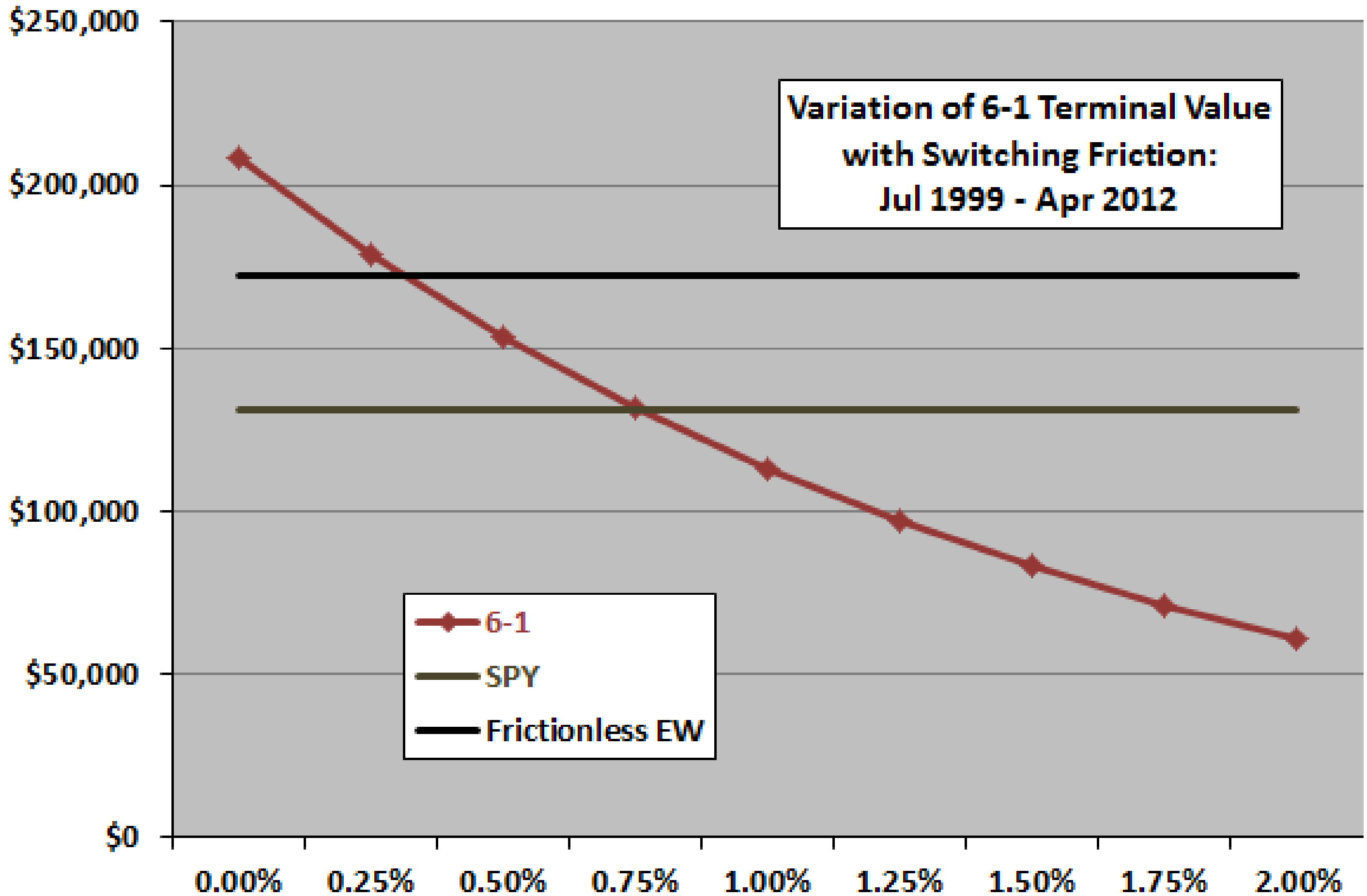
The next chart shows the net monthly return for the 6-1 strategy minus same-month EW portfolio return over the available sample period, along with a trend line. The trend line slopes downward into negative values, suggesting that the 6-1 strategy adds value to simple diversification early in the sample period but is a drag later. However, the sample period is short and monthly relative returns highly variable.

How does the terminal value of the 6-1 strategy vary with assumed level of switching friction?



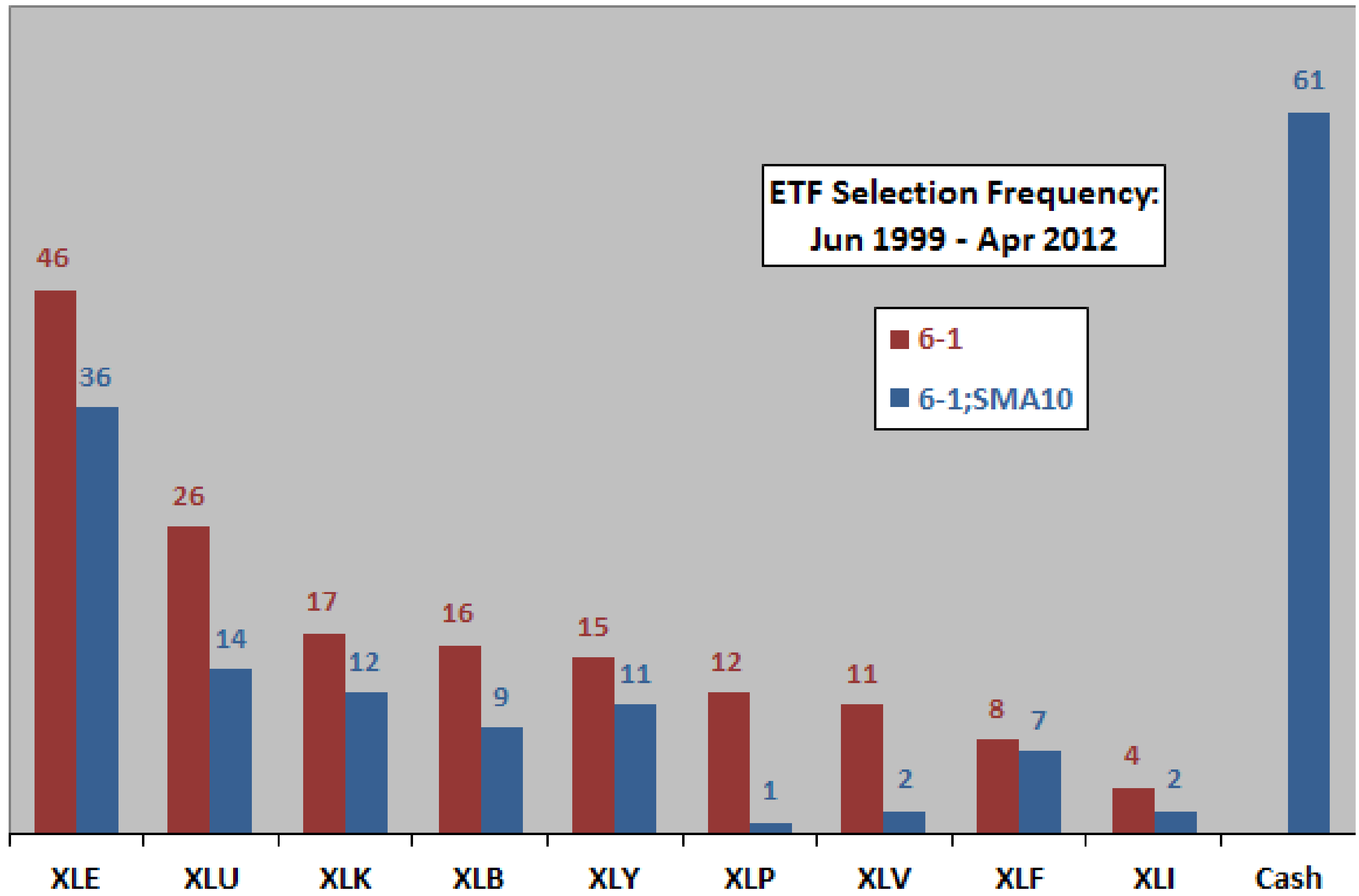
The next chart plots the terminal value of the 6-1 strategy for switching frictions ranging from 0.00% to 2.00%, along with the fixed terminal values of buying and holding SPY and holding the frictionless EW portfolio. Results indicate that the 6-1 strategy beats SPY at easily achievable levels of switching friction and the EW portfolio benchmark at lower but achievable levels of switching friction.

How does the alternative 6-1;SMA10 strategy compare?



The next chart compares the distributions of sector ETF winners/Cash for the 6-1 and 6-1; SMA10 strategies. The latter is in Cash for 61 of the 155 monthly winners (39%). Several sectors become almost irrelevant for the 6-1;SMA-10 strategy.

How does applying the 6-1;SMA10 strategy translate into cumulative returns?

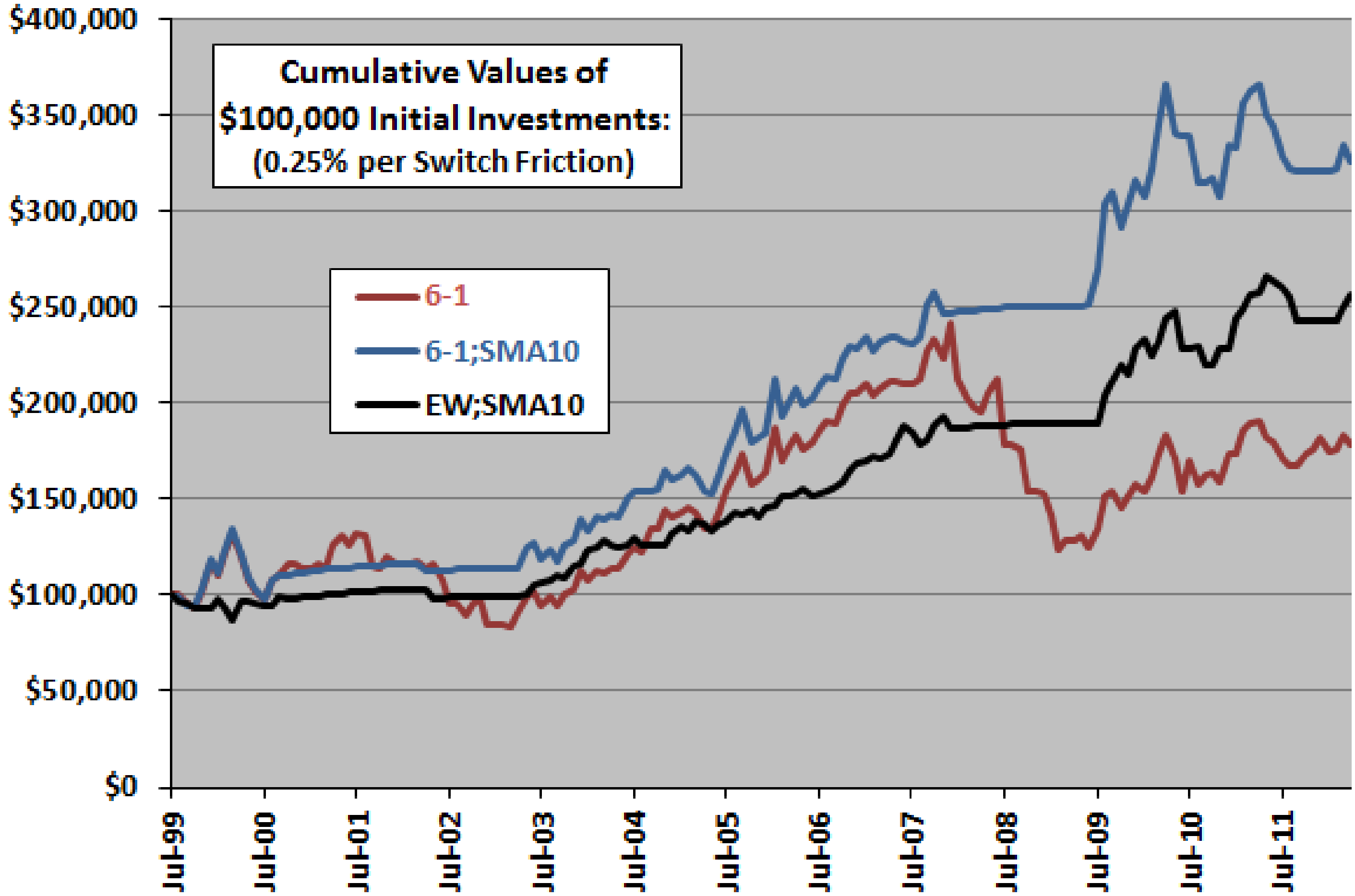


The final chart compares the cumulative values of $100,000 initial investments in the 6-1 strategy, the 6-1;SMA10 strategy and a benchmark EW:SMA10 strategy that holds the EW portfolio (goes to cash) when the S&P 500 Index is above (below) its 10-month simple moving average. As above, calculations derive from the following assumptions:

- Reallocate/rebalance at the close on the last trading day of each month (assume that values and total six-month past returns for the ETFs, and the S&P 500 Index 10-month simple moving average, can be calculated just before the close).
- Switching friction for the 6-1 and 6-1;SMA10 strategies is 0.25% of the balance whenever there is a change in holdings, but EW portfolio rebalancing is frictionless for conservative benchmarking.
- Ignore any tax implications of trading.

The 6-1;SMA10 strategy generally outperforms the 6-1 strategy based on avoidance of most of major downturns. It also consistently provides an edge over EW;SMA10, indicating that sector ETF momentum adds value to simple diversification during bull markets.

For reference, the average monthly gross return for the 6-1;SMA10 (6-1) strategy is 0.93% (0.64%), with standard deviation of monthly returns 4.30% (5.80%) and and return-risk ratio 0.22 (0.11). Comparable statistics for EW;SMA10 are 0.64%, 2.52% and 0.26.



In summary, *evidence from a limited sample period suggests that a simple sector ETF momentum strategy fares well compared to the overall stock market and adds some value to a simple (equal-weighted) diversification approach, but this added value may be dissipating.*

For robustness tests and consideration of additional strategy variations, see "Simple Sector ETF Momentum Strategy Robustness/Sensitivity Tests", "Alternative Sector ETF Momentum Metrics" and "Hedges/Shorting to Exploit Sector ETF Momentum?".

Cautions regarding findings include:

- Sample size is modest (just 27 independent six-month momentum ranking intervals and about 16 independent 10-month SMA intervals).
- The selected ETF ranking interval derives from prior academic studies that most often use six-month and 12-month ranking intervals, with one-month holding intervals. This prior research may impound (and therefore transmit) data snooping bias, which is especially pernicious for small samples. Ranking intervals other than six months and holding periods other than one month may produce different results. For the above tests, using longer ranking and holding intervals would effectively reduce the already-small sample size. Optimizing the ranking and holding intervals would elevate data snooping bias.
- Including ETFs representing other asset classes (such as bonds, commodities, equity styles and international stocks) may enhance results, but may also increase number of position switches and therefore cumulative trading friction.

- Potential wildness in ETF monthly return distributions limits confidence in results.

Originally published at http://www.cxoadvisory.com/4400/momentum-investing/simple-sector-etf-momentum-strategy-performance/ on May 7, 2012.

Melding Momentum, Diversification and Absolute Return

April 23, 2012

What is the safest way to exploit asset price momentum? In his April 2012 paper entitled "Risk Premia Harvesting Through Momentum" (the National Association of Active Investment Managers' 2012 Wagner Award winner with different title), , Gary Antonacci investigates systematic capture of upside volatility at the asset class level via a momentum/diversification/absolute return strategy that:

- Exploits momentum via long positions in winners, based on 12-month lagged total returns with no skip month, re-evaluated monthly.
- Maintains diversification by:
  - Using indexes rather than individual securities; and,
  - Holds the equally weighted winners from each the following pairs of competing indexes: gold versus long-term Treasury bonds; U.S. equities versus foreign equities; high yield bonds versus intermediate credit bonds; and equity real estate investment trusts (REIT) versus mortgage REITs.
- Mitigates risk by substituting Treasury bills (T-bills) for each pairwise winner that has not outperformed T-bills during the 12-month ranking interval.

Using monthly total returns for indexes constructed from targeted classes of equities, bonds, REITs and spot gold, along with contemporaneous 90-day Treasury bill yields, during January 1974 (or the earliest available) through December 2011, *he finds that:*

For each pair of asset classes separately (see the chart below):

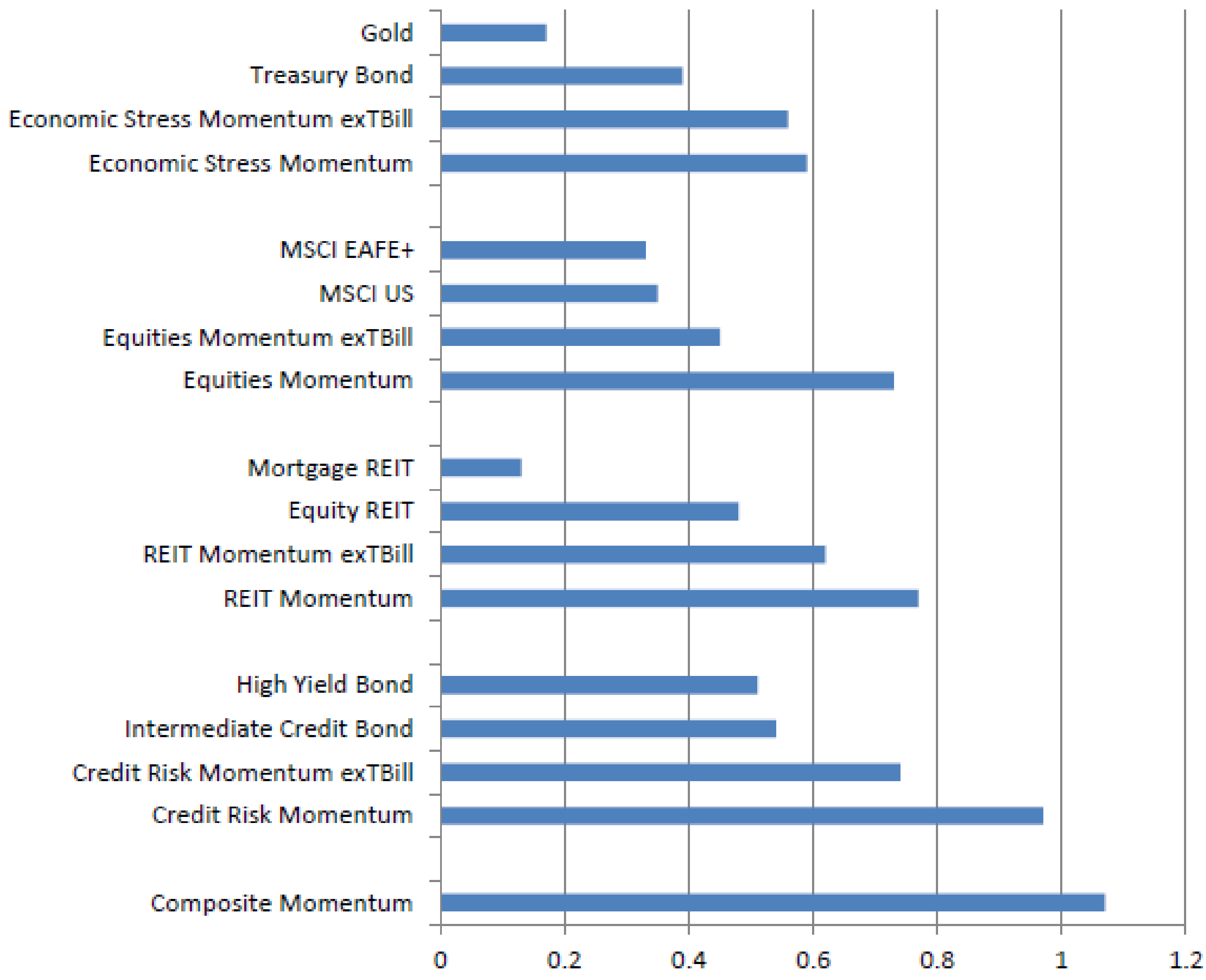
- A strategy of picking the momentum winner improves gross risk-adjusted performance as measured by Sharpe ratio compared to the two competing asset class indexes.
- Augmenting this strategy by substituting T-bills for any pair winner that underperforms T-bills during the momentum ranking interval further increases gross Sharpe ratio and mostly reduces maximum annual drawdown.
- A composite strategy that holds the equally weighted pairwise winners (or T-bills for those winners that have underperformed T-bills) further boosts gross Sharpe ratio with very low maximum annual drawdown. This composite strategy easily outperforms an equally weighted portfolio of all asset classes plus T-bills.
- Switching frictions are low, with the average number of switches per year ranging from just 1.2 for high yield bonds versus intermediate credit bonds to 1.6 for gold versus long-term Treasury bonds and equity REITs versus mortgage REITs.
- Implementing the asset class indexes as tradable assets is not very costly, because the

average annual expense ratio for corresponding exchange-traded funds (ETF) is about 0.25%.
- Results are generally robust to subperiods and use of six-month rather than 12-month past returns.

The following chart, taken from the paper, summarizes gross Sharpe ratios for:

- Each of the eight asset class indexes.
- A simple momentum strategy that each month picks the winner of paired assets (exTBill) based on lagged 12-month total return.
- A risk-mitigated version of the momentum strategy that substitutes T-bills for a pairwise winner that has not outperformed T-bills during the 12-month ranking interval.
- A composite strategy that each month equally weights the four risk-mitigated momentum winners.

Results demonstrate improvement from momentum, risk mitigation via an absolute return requirement and risk mitigation via diversification across asset class pairs.



In summary, *evidence from backtesting with asset class indexes indicates that melding return momentum, diversification and an absolute return requirement enhances investment performance.*

Cautions regarding findings include:

- Reported returns are gross, not net. While turnover of asset class proxies is low, the implication that current asset class ETF average annual expense ratios are representative of the frictions involved in translating indexes to tradable assets for backtesting is arguable:
  - Such expense ratios might have been higher early in the sample period.
  - Annual expense ratios do not include the trading frictions (broker fees, bid-ask spreads) involved in constructing fund portfolios. While frictions decline considerably in recent times, they are likely substantial during the early part of the sample period (see “Trading Frictions Over the Long Run”) and may still be material.
- Easy retail access to asset class diversification and asset class momentum strategies via ETFs may intensify competition for associated benefits and thereby increase asset class return correlations (reducing diversification benefits) and reduce momentum returns.
- Complex strategies may carry material data snooping bias, both direct (for example, from picking asset class pairs) and indirect (from data snooping in relevant prior research).

See also “Simple Asset Class ETF Momentum Strategy”, which includes cash (at the T-bill yield) as an asset class, thereby ensuring that the winner asset has a positive lagged return (but very rarely picking cash).

Originally published at http://www.cxoadvisory.com/20707/momentum-investing/melding-momentum-diversification-and-absolute-return/ on April 23, 2012.

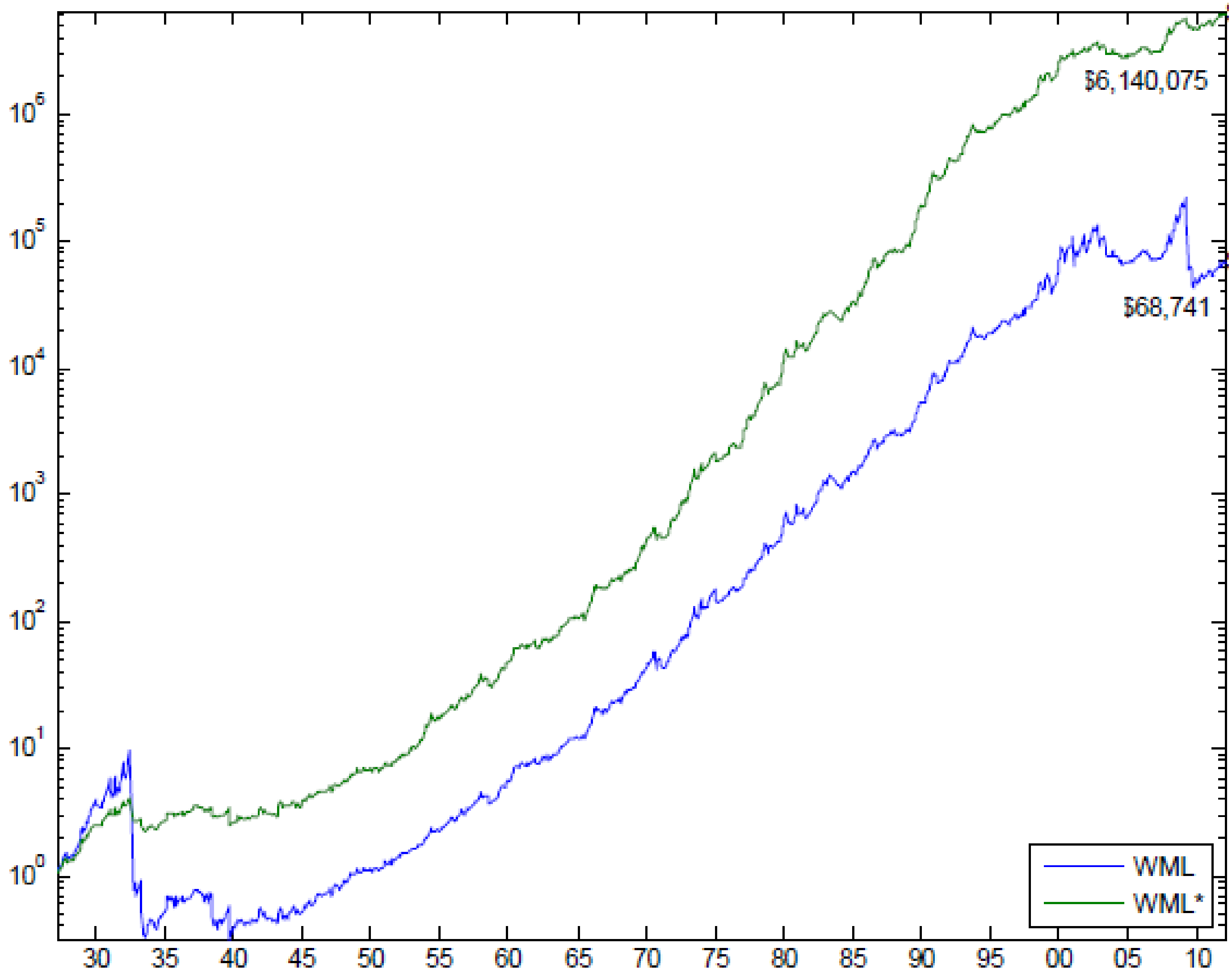
Avoiding Momentum Strategy Crashes

April 20, 2012

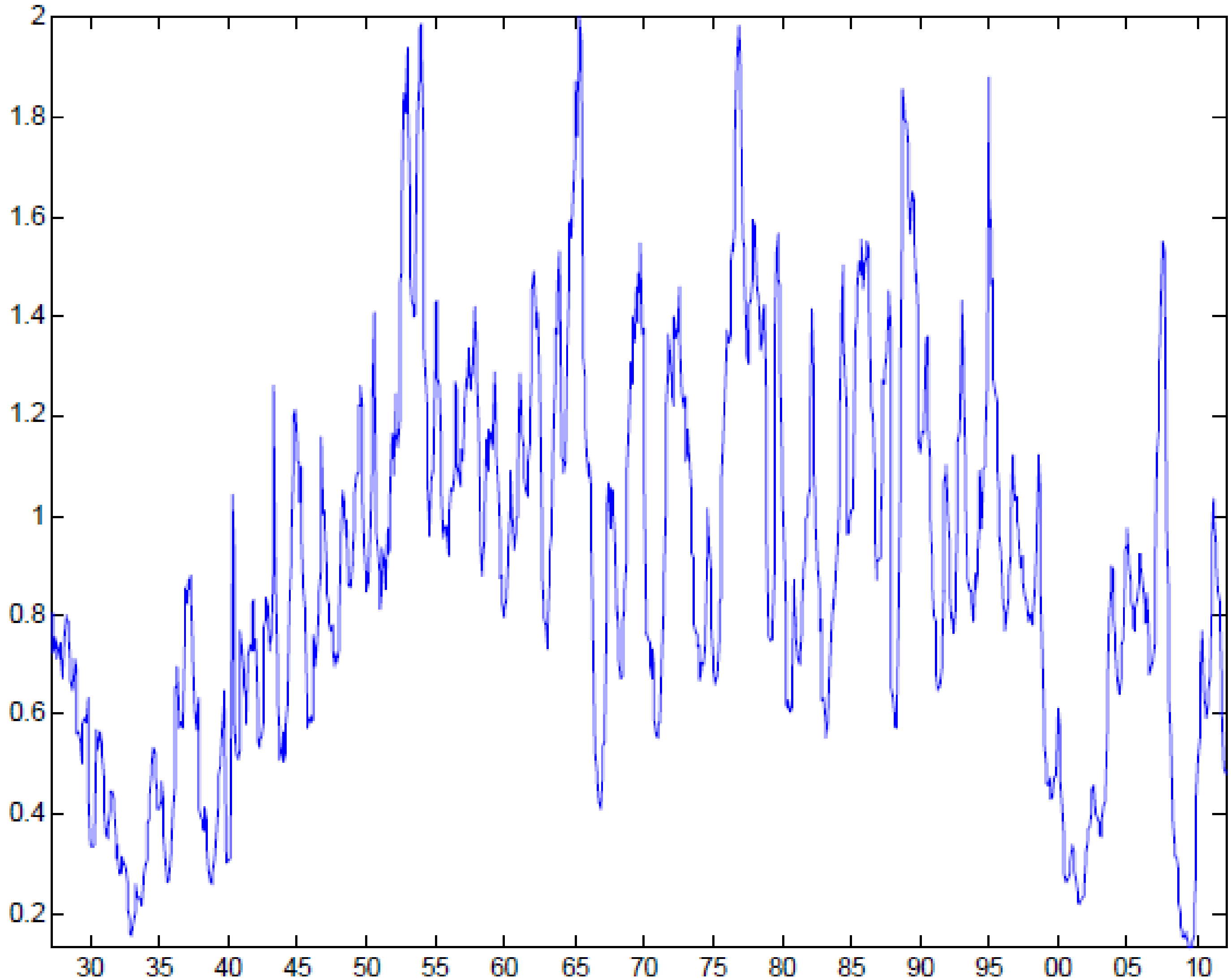
Stock price momentum strategies sometime crash, greatly detracting from long-term performance. Is there a reliable way to avoid the crashes? In the April 2012 version of their paper entitled "Managing the Risk of Momentum", Pedro Barroso and Pedro Santa-Clara investigate usefulness of momentum portfolio volatility as a crash protection signal. They construct a momentum portfolio return series based on equal allocations to the risk-free asset (one-month Treasury bill), a value-weighted long side of momentum winners and a value-weighted short side of momentum losers, reformed and rebalanced monthly. They measure momentum for all NYSE/AMEX/NASDAQ stocks based on 11-month lagged returns plus a skip-month, and define winners and losers based on the top and bottom decile cutoffs for NYSE stock momentum. Using daily and monthly momentum portfolio returns and monthly U.S. equity risk factors (market, size, book-to-market) based on stock prices for July 1926 through December 2011, *they find that:*

- Over the entire sample period, the specified momentum portfolio generates an average gross abnormal (adjusting for market, size and book-to-market factors) return of 1.75% per month (21% per year).
- However, the return distribution for this portfolio has a very fat left tail (material crash risk), making it unappealing to risk-averse investors. For example, during July-August 1932 and March-May 2009, the portfolio loses 91.6% and 73.4% of its value, respectively.
- Two aspects of momentum portfolio return volatility support its use in constructing a crash protection signal:
  - It is highly persistent, with an R-squared of 0.58 for a monthly autoregression (portfolio volatility last month explains 58% of portfolio volatility next month).
  - It is substantially distinct from overall stock market volatility, which accounts for only 23% of momentum portfolio volatility.
- Scaling the monthly long-short allocations in the specified momentum portfolio according to the inverse of the volatility of its daily returns over the past six months (with annualized volatility target 12%) greatly enhances its performance over the sample period:
  - Average annualized gross return increases from 14.5% to 16.5%.
  - Standard deviation of annual gross returns decreases from 27.5% to 17.0%.
  - Gross Sharpe ratio nearly doubles from 0.53 to 0.97.
  - Worst one-month gross return improves from -80.0% to -28.4%.
  - Worst annual gross drawdown improves from -97.0% to -45.2%.
- Results are generally robust to other ways of measuring realized volatility of the momentum portfolio.

The following chart, taken from the paper, compares on a logarithmic scale the long-run gross cumulative performance of $1 initial investments in: (1) the baseline momentum portfolio as described above (WML); and, (2) the portfolio with crash protection based on scaling long and short sides according to the inverse of daily portfolio volatility over the previous six months with an annualized volatility target of 12% (WML*). The chart shows that the latter outperforms largely by avoiding much of the impacts of a few momentum crashes, dramatically improving terminal value from $68,741 to $6,140,075.



The next chart, also from the paper, summarizes values of the monthly scale factor applied to the long and short sides of the momentum portfolio with crash protection over the sample period, as derived from inverse of the volatility of daily portfolio returns over the previous six months and an annualized volatility target of 12%. The scale factor has an average value of 0.90 and a range of 0.13 to 2.00, with lows evident during the early 1930s, 2000-02 and 2008-09.



In summary, *evidence suggests that scaling investment in a hedged momentum portfolio of individual U.S. stocks based on the inverse of lagged volatility of the momentum portfolio (not the market) substantially boosts performance, mostly via crash avoidance.*

Cautions regarding findings include:

- Reported returns are gross, not net. Momentum strategies tend to generate high portfolio turnover, and changing monthly leverage would amplify turnover and associated trading frictions. Large dispositions down to very low values of the scale factor may occur when the U.S. equity market is highly illiquid and trading frictions are extremely high.
- The study does not consider the cost and feasibility of shorting losers.
- The paper states: “As WML [the specified momentum portfolio] is a zero-investment and self-financing strategy we can scale it without constraints.” However, the market may place constraints on long-short position size in the form of trading friction (bid-ask spread and impact of trading on price) and availability of shares for shorting. For a long-only strategy, portfolio management would be problematic in terms of both capital reserve and cost of leverage.
- While much of benefit comes from avoiding big crashes, there are (by definition) very few big crashes for testing. Very small samples undermine confident inference and elevate

any data snooping bias derived from exploring alternative crash protection signals.

Originally published at http://www.cxoadvisory.com/20697/momentum-investing/avoiding-momentum-strategy-crashes/ on April 20, 2012.

Spectacular “New” Momentum and Reversal?

April 2, 2012

Do “new” momentum stocks outperform “old” ones? In the March 2012 version of their paper entitled “Limited Attention, Salience, and Stock Returns”, Avanidhar Subrahmanyam, Jason Wei and Hsin-Yi Yu analyze whether stocks newly entering and exiting extreme momentum deciles exhibit unusual future returns because of heightened investor attention. Their benchmark (6-6) strategy consists of conventional overlapping winner-minus-loser momentum portfolios that are long/short those stocks with the highest/lowest returns over the past six months, formed monthly (after a skip-month) and held for six months. They classify a stock as a 6-6 arriver if it is not in any of the five preceding overlapping winner-minus-loser portfolios and a 6-6 dropper if it was in at least one winner-minus-loser portfolio active during the previous five months but is not in any of the active portfolios this month. They also consider arriving and dropping stocks defined relative to ranking intervals of 3, 9 and 12 months and holding intervals of 1, 2, 3, 9 and 12 months. Within portfolios, they weight the winner and loser sides equally and each stock within the winner or loser side equally. Using daily and monthly prices and volumes for NYSE, AMEX and NASDAQ common stocks priced above $5, along with contemporaneous risk factor and robustness test data as available, during 1962 through 2010, *they find that:*

- 6-6 arrivers to both winners (decile 10) and losers (decile 1) perform very well the next month (over 3% return), but performance then quickly diminishes. The outperformance of new winners arriving from deciles 1, 2 and 3 is especially short-lived. New losers arriving from deciles 2, 3 and 4 outperform new winners, indicative of strong reversals.
- 6-6 droppers from both winners and losers generally perform poorly the next month, with mostly negative three-factor (market, size, book-to-market) alphas.
- The average number of monthly winners (losers) for the baseline 6-6 strategy is 822 (890), with about 21% or 169 (21% or 185) on the move each month.
- While not differing appreciably in size, arrivers and droppers tend to be relatively volatile. Arrivers have an average bid-ask spread of roughly 2.5% (close to the average for all stocks in the sample), while droppers have a relatively large average bid-ask spread of roughly 4.5%.
- Strategies that concentrate on the extreme returns of arrivers and droppers are much more profitable than conventional momentum strategies (see the chart below). For example, over the entire sample period, the average monthly gross return and Sharpe ratio for a portfolio that is each month long (short) 6-6 loser decile arrivers (6-6 loser decile droppers) are 3.6% and 0.65, respectively, compared to 1.2% and 0.26 for a conventional 6-6 momentum strategy.
- Further enhancement derives from focusing on loser arrivers from deciles 2, 3 and 4 and loser droppers to deciles 2, 3 and 4 (an average of 52 arrivers and 15 droppers per month). Over the entire sample period, the average monthly gross return and Sharpe ratio for a portfolio that is each month long (short) such a restricted portfolio of 6-6 loser

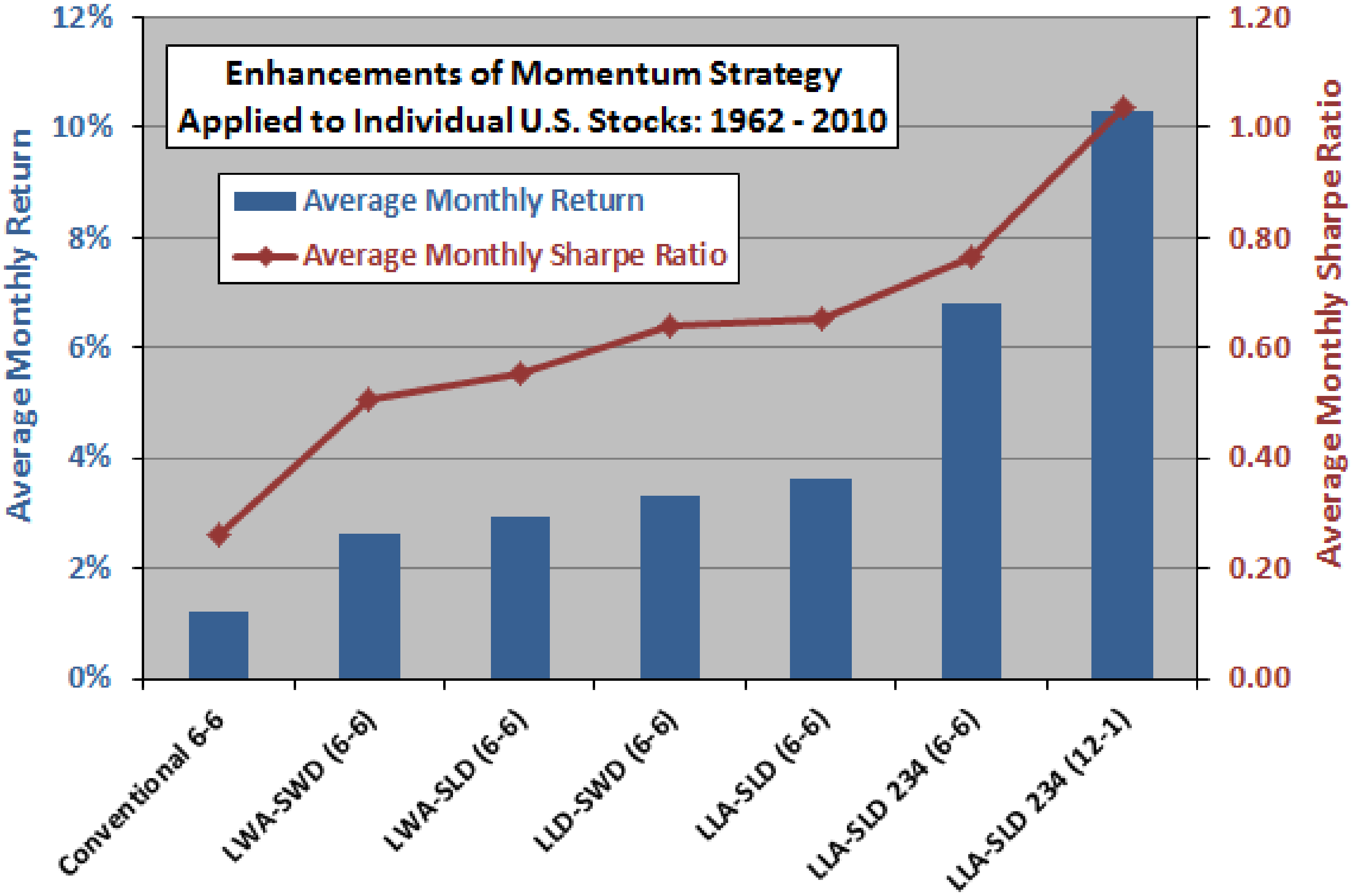
decile arrivers (6-6 loser decile droppers) are 6.8% and 0.76, respectively. Defining arrivers and droppers relative to a 12-1 (rather than 6-6) baseline momentum strategy boosts average monthly gross return and Sharpe ratio to 10.3% and 1.03.

- Enhanced momentum strategy results are robust to:
  - Dropping the skip-month between baseline strategy ranking and holding intervals. In fact, profitability is generally higher without the skip-month, as suggested by the rapidly fading returns of arrivers and droppers.
  - Exclusion of January from calculations. While January returns are relatively strong for the enhanced strategies, performance in other months is very good.
  - Different subperiods. In fact, there is steady improvement in enhanced strategy returns over time. During 2001-2010, the average monthly gross return and Sharpe ratio for a portfolio that is each month long (short) a portfolio of 12-1 loser decile arrivers from deciles 2, 3 and 4 (12-1 loser decile droppers to deciles 2, 3 and 4) are 16.4% and 1.05, respectively.
  - Listing exchange and firm size, although NASDAQ stocks perform more impressively than NYSE/AMEX stocks.
- Based on available data, there is abnormally high short-term buying pressure for arrivers that reverses in the longer run, supporting the explanation that arrivers attract retail investor attention.

The following chart, constructed from data in the paper, summarizes monthly average gross returns and Sharpe ratios for momentum strategies focused on stocks newly arriving to or newly dropping from extreme past-return deciles. The baseline strategy and enhanced strategies are:

- Conventional 6-6: long winners and short losers (overlapping, with skip-month)
- LWA-SWD (6-6): long winner arrivers and short winner droppers (6-6 baseline)
- LWA-SLD (6-6): long winner arrivers and short loser droppers (6-6 baseline)
- LLD-SWD (6-6): long loser arrivers and short winner droppers (6-6 baseline)
- LLA-SLD (6-6): long loser arrivers and short loser droppers (6-6 baseline)
- LLA-SLD 234 (6-6): long loser arrivers and short loser droppers, from/to deciles 2, 3 or 4 only (6-6 baseline)
- LLA-SLD 234 (12-1): long loser arrivers and short loser droppers, from/to deciles 2, 3 or 4 only (12-1 baseline)

Results indicate that concentrating long positions on stocks newly arriving to the loser decile from nearby deciles and short positions on stocks newly departing from the loser decile to nearby deciles considerably improves momentum strategy performance.



In summary, *evidence indicates that U.S. equity investors may be able to improve momentum strategy returns considerably by concentrating long (short) positions in stocks newly entering (exiting) the 10% of stocks with the worst past returns, with the entries and exits not deriving from violent short-term action.*

Cautions regarding findings include:

- Reported returns and Sharpe ratios are gross, not net. Incorporating reasonable trading frictions, which tend to be relatively high for momentum strategies due to high turnover, would reduce them. Trading frictions (bid-ask spreads) may be exceptionally high for the short side of the best portfolios. Persistence into recent low-friction subsamples mitigates.
- Reported returns and Sharpe ratios also do not consider the feasibility and cost of shorting targeted stocks. Shorting limitations and costs would reduce profitability.
- The intricacy of definitions and the large number of combinations tested introduce data snooping bias, such that the best combinations may substantially overstate reasonable expectations for real trading.

See also "Exploiting Momentum While Avoiding Long-term Reversal" for related research.

Originally published at http://www.cxoadvisory.com/20600/momentum-investing/spectacular-

new-momentum-and-reversal/ on April 2, 2012.

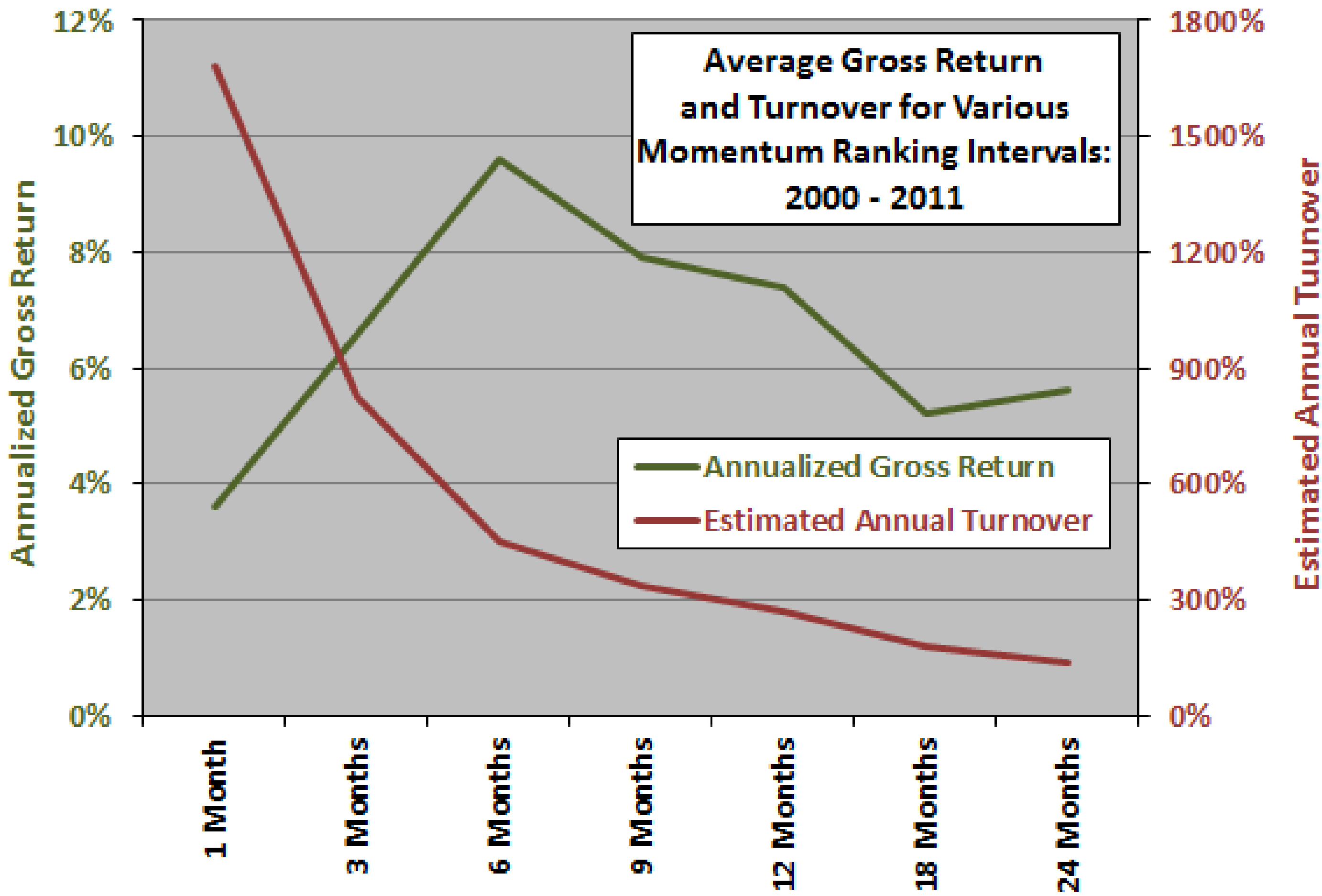
Melding Momentum and ETF Portfolio Management Practices

March 28, 2012

It is arguable that many exchange-traded fund (ETF) momentum strategy tests derive more from logical/programming simplicity than common portfolio management practices. Does momentum work for portfolios of ETFs when melded with the latter? In his March 2012 paper entitled "Tactical Asset Allocation Using Relative Strength", John Lewis tests ETF momentum in the context of real-world portfolio practices. He employs a universe of nearly 100 ETFs encompassing U.S. equity sectors and styles, international/global equities, bonds, commodities, real estate and currencies, including some inverse funds. After initial selection of top ETFs, he replaces weakening funds with strong ones as needed based on daily (or weekly) prices rather than at a fixed interval, depending on four parameters: (1) momentum ranking interval; (2) number of ETFs in the portfolio; (3) buy rank threshold; and, (4) sell rank threshold. To test robustness, he conducts multiple trials based on random selection of ETFs above the buy rank threshold. Specifically, he presents seven examples of 100 iterations of 10-ETF portfolios randomly selected from the top 25% of the ETF universe based on momentum ranking intervals of one month to two years, replacing ETFs when they fall out of the top 25%. Portfolios are apparently equally weighted at initial formation. Examples ignore dividends, management fees and trading frictions. Using daily returns for the ETFs from the end of 1999 through the end of 2011 (12 years), *he finds that:*

- For the featured 6-month ranking interval over the entire sample period:
  - Average (median) gross return for the 100 portfolio trials is 199% (197%), compared to -14% for the S&P 500 Index, 112% for a fixed income market aggregate and 74% for a 60/40 mix of stocks/bonds.
  - The gross return for the worst trial is 122%, still beating all three benchmarks.
  - During 2005-2007 (2011), all (none) of the 100 trial portfolios beat all (any) of the three benchmarks.
- For ranking intervals of three, six, nine and 12 months, all 100 trial portfolios beat the S&P 500 Index over the entire sample period, with average annualized gross returns of 6.6%, 9.6%, 7.9% and 7.4%, respectively.
- Average gross returns for portfolios formed using ranking intervals of one, 18 and 24 months are notably weaker (especially the one-month ranking interval) than those using intervals of three to 12 months.
- Turnover escalates as ranking interval decreases, indicating a critical trade-off between responsiveness to trend change and trading friction for ranking intervals in the range of six to 12 months.

The following chart, representative of findings in the paper, compares the annualized average gross return and estimated average annual turnover of the ETF momentum strategy described above by ranking interval. While a six-month ranking interval maximizes average gross return, a longer ranking interval with lower turnover may maximize average net return.



In summary, *evidence from tests of ETF momentum in a portfolio management context support belief that ranking intervals in the range three to 12 months outperform simple benchmarks over the past 12 years.*

Cautions regarding findings include:

- Many of the ETFs in the specified universe do not exist over much of the test period. Per the author's disclosure: "Index data was used for some indexes before ETF price data was available." Indexes do not include the costs of forming tradable assets, which may be material (especially for inverse funds).
- The large ETF universe likely includes groups with highly correlated returns (redundant assets), such that incremental diversity benefit may not offset the higher trading frictions for a more finely divided portfolio.
- As noted above (and in the author's disclosure), "models do not reflect the reinvestment of dividends" and "returns of the models do not reflect any management fees, transaction costs, or other expenses that would reduce the returns of an actual portfolio." Including realistic fees and trading frictions would reduce returns, perhaps decisively for portfolios of modest value.
- Assessment of the timing ability of tactical asset class allocation requires a benchmark encompassing the same set of assets, such as value-weighted or equal-weighted

portfolios of the ETF universe (or a randomly selected subset). The equally weighted, occasionally rebalanced ETF universe may be stiff competition for the average momentum portfolio.

See “Melding Momentum and Stock Portfolio Management Practices” for a comparable approach using U.S. stocks. See “Simple Asset Class ETF Momentum Strategy” for a simplified momentum approach involving ETFs as asset class proxies.

Originally published at http://www.cxoadvisory.com/20533/momentum-investing/melding-momentum-and-etf-portfolio-management-practices/ on March 28, 2012.

Interaction of Momentum/Reversal with Size and Value

March 12, 2012

Do market capitalization (size) and book-to-market ratio systematically affect intermediate-term momentum and long-term reversal for individual stocks? In their February 2012 paper entitled "Momentum and Reversal: Does What Goes Up Always Come Down?", Jennifer Conrad and Deniz Yavuz examine whether size and book-to-market ratio interact with momentum portfolio performance over intervals of 0-6, 6-12, 12-24 and 24-36 months after formation. They designate a stock as a winner (loser) if its 6-month lagged return is higher (lower) than the average for all stocks, with a skip-month before portfolio formation. They weight stocks within momentum portfolios by the absolute difference between its lagged 6- month return and that of all stocks, normalizing so that winner and loser sides contribute equally. They define three hedge portfolio types to measure risk factor-momentum interaction:

1. MAX portfolios are long (short) past winners that are small and/or high book-to-market (losers that are large and/or low book-to-market).
2. MIN portfolios are long (short) past winners that are large and/or low book-to-market (losers that are small and/or high book-to-market).
3. ZERO portfolios are long (short) past winners (losers) with similar size and book-to-market characteristics.

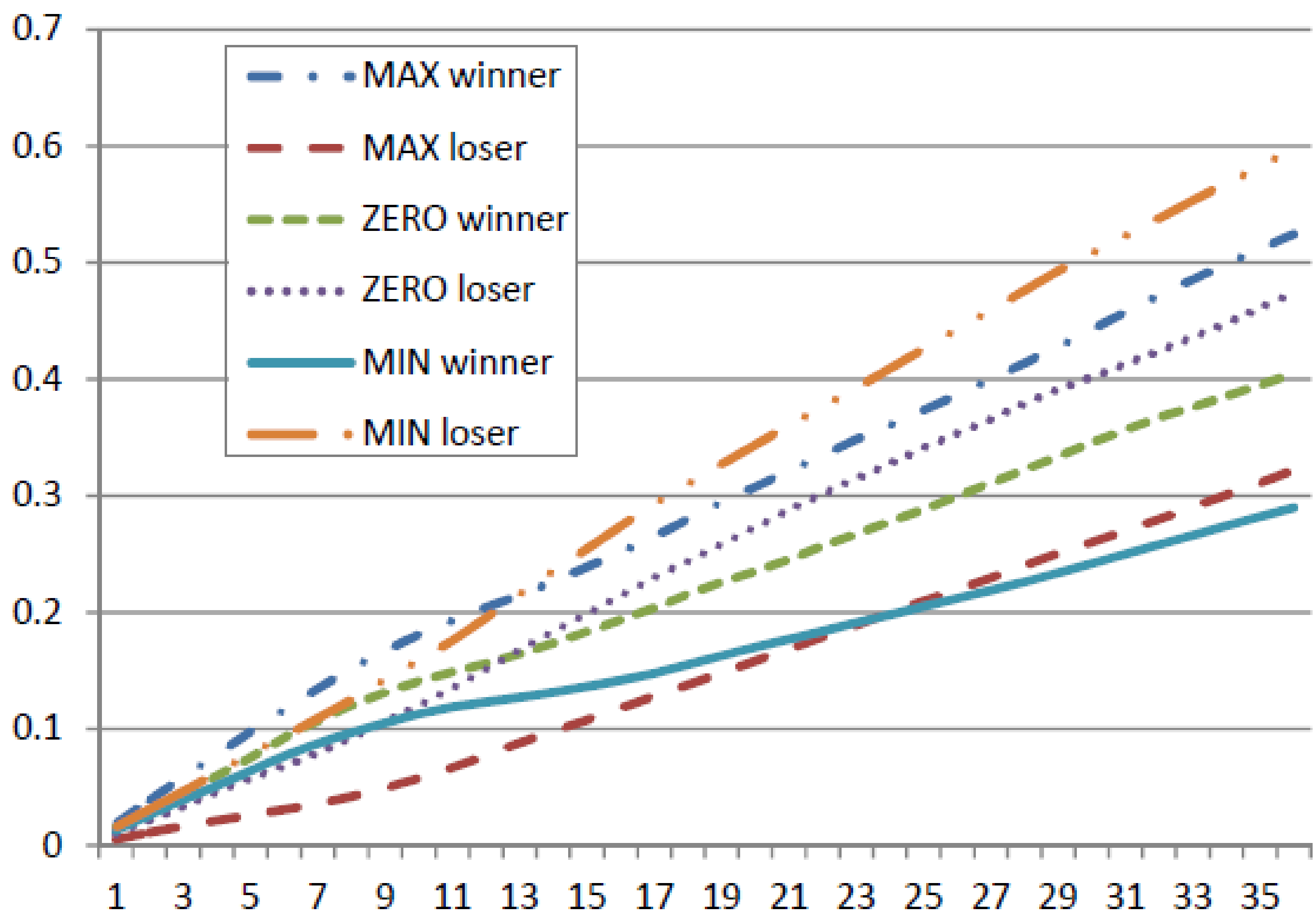
They sort stocks by size and book-to-market into thirds. When combining factors, they define stocks as high (low) risk group if they are in the high-risk (low-risk) third for one factor and in or above (below) the middle-risk third for the other. Using returns and factor characteristics for a broad sample of U.S. stocks during 1965 through December 2010, *they find that:*

- Over the entire sample of stocks, past winners earn an average monthly gross return of 1.52% over the next six months, and a hedge portfolio that is long past winners and short past losers generates an average monthly gross return of 0.50% and an average monthly gross three-factor alpha (market, size, book-to-market) of 0.65%. Average monthly gross returns are -0.11%, -0.36% and -0.16% during months 6-12, 12-24 and 24-36 after portfolio formation, respectively.
- MAX and MIN hedge portfolios exhibit very different cumulative return patterns, driven by both the winner and loser sides. For example, when combining size and book-to-market sorts:
  - The MAX portfolio generates average monthly gross returns of 1.31% during months 0-6 and 0.49% during months 6- 12, with no evidence of reversal over the next 24 months.
  - The MIN portfolio generates average monthly gross returns of -0.18 %, -0.66%, -0.73% and -0.33% during months 0-6, 6-12, 12-24 and 24-36, respectively.

- ZERO portfolio performance lies between those of the MAX and MIN portfolios for every interval.
- More generally, momentum portfolios whose winner (loser) stocks have high (low) expected returns based on size and book-to-market ratio generate significant momentum profits with no subsequent reversals. Momentum portfolios whose winner (loser) stocks have low (high) expected returns based on these factors generate no significant momentum profits with strong reversals.

The following chart, taken from the paper, plots the cumulative gross returns of the average winner and loser sides of MAX, MIN and ZERO hedge portfolios during the 36 months after portfolio formation. This breakdown underlies the momentum and reversal behaviors of the hedge portfolios. For example:

> The winner (loser) side of the MAX portfolio is very strong (weak) during the first nine months. Both sides subsequently follow trajectories with approximately equal slopes. The hedge portfolio therefore exhibits significant intermediate-term momentum with no reversal.
>
> In contrast, the winner (loser) side of the MIN portfolio has a moderate (relatively strong) start over the first nine months, and then fades to relative weakness (maintains relative strength). The hedge portfolio therefore exhibits no intermediate-term momentum with significant reversal.



In summary, *evidence indicates that investors may be able to amplify intermediate-term momentum and long-term reversal of individual stocks by combining a momentum factor with size and book-to-market factors.*

Cautions regarding findings include:

- Reported portfolio returns are gross, not net. Including reasonable trading frictions would lower these returns and, especially because small stocks tend to have higher frictions, may affect findings.
- Proliferation of portfolios introduces data snooping bias, mitigated by systematic progressions across the three portfolio types.

Compare this approach with that described in "Exploiting Momentum While Avoiding Long-term Reversal".

Originally published at http://www.cxoadvisory.com/20045/size-effect/interaction-of-momentumreversal-with-size-and-value/ on March 12, 2012.

Testing U.S. Equity Anomalies Worldwide

February 24, 2012

Do widely acknowledged U.S. equity market anomalies exist in other stock markets? If so, why? In his November 2011 paper entitled "Equity Anomalies Around the World", Steve Fan investigates whether a number of equity market anomalies found among U.S. stocks (asset growth, book-to-market ratio, investment-to-assets ratio, six-month momentum with skip-month, net stock issuance, size and total accruals) also occur in other equity markets and the degree to which such anomalies relate to stock-unique (idiosyncratic) risk. He measures raw anomaly strength based on gross returns from hedge ("zero-cost") portfolios that are long and short equally weighted extreme quintiles of stocks ranked annually for each accounting variable and every six months for momentum (with overlapping momentum portfolios). To estimate alphas, he adjusts raw returns for the three Fama-French risk factors (market, book-to-market, size) or three alternative investment-based risk factors (market, investment, return on assets). Using monthly common stock return data and associated firm characteristics/accounting data for 43 country stock markets during 1989 through 2009, *he finds that:*

- There are significant average monthly gross returns for hedge portfolios formed using:
  - High-minus-low book-to-market ratio, high-minus-low momentum and small-minus-large size in most countries (24 to 36 out of 43).
  - Low-minus-high asset growth, low-minus-high investment-to-assets ratio, low-minus-high net stock issuance and low-minus-high total accruals in some countries (10 to 18 out of 43).
- Developed countries exhibit higher gross hedge returns for asset growth, momentum and net stock issuance, while emerging countries have higher returns for book-to-market ratio and investment-to-assets ratio.
- Most of these anomalies persist after controlling for the risk factors from the Fama-French model and the alternative three-factor model.
- Idiosyncratic volatility/risk (an indicator of the cost of trading) relates positively to abnormal returns for all of the anomalies, more weakly in developed than emerging countries. In other words:
  - Stocks with high (low) idiosyncratic risk tend to exhibit high (low) abnormal returns. Notably, abnormal returns for stocks with very low idiosyncratic risk are generally insignificant.
  - Investors take more risk to exploit anomalies in developed than emerging markets.

In summary, *evidence from 43 country stock markets over two recent decades indicates that individual stock anomalies found in the U.S. exist at the gross level in some to many other countries, but costs of trading the anomalies may preclude profitable exploitation.*

Cautions regarding findings include:

- Reported returns are gross, not net. Including realistic trading frictions and shorting costs from hedge portfolio formation/reformation would reduce returns. Estimating and incorporating trading frictions would arguably be an alternative to idiosyncratic risk as a way of investigating limits to arbitrage for the anomalies.
- As noted in the study, results are full-sample only, with no assessment of whether the anomalies weaken over time.
- A sample size of 21 years may not be large with respect to number of economic cycles or secular economic trends (such as disinflation since the early 1980s).
- Data quality may vary materially by market.

Originally published at http://www.cxoadvisory.com/19828/fundamental-valuation/testing-u-s-equity-anomalies-worldwide/ on February 24, 2012.

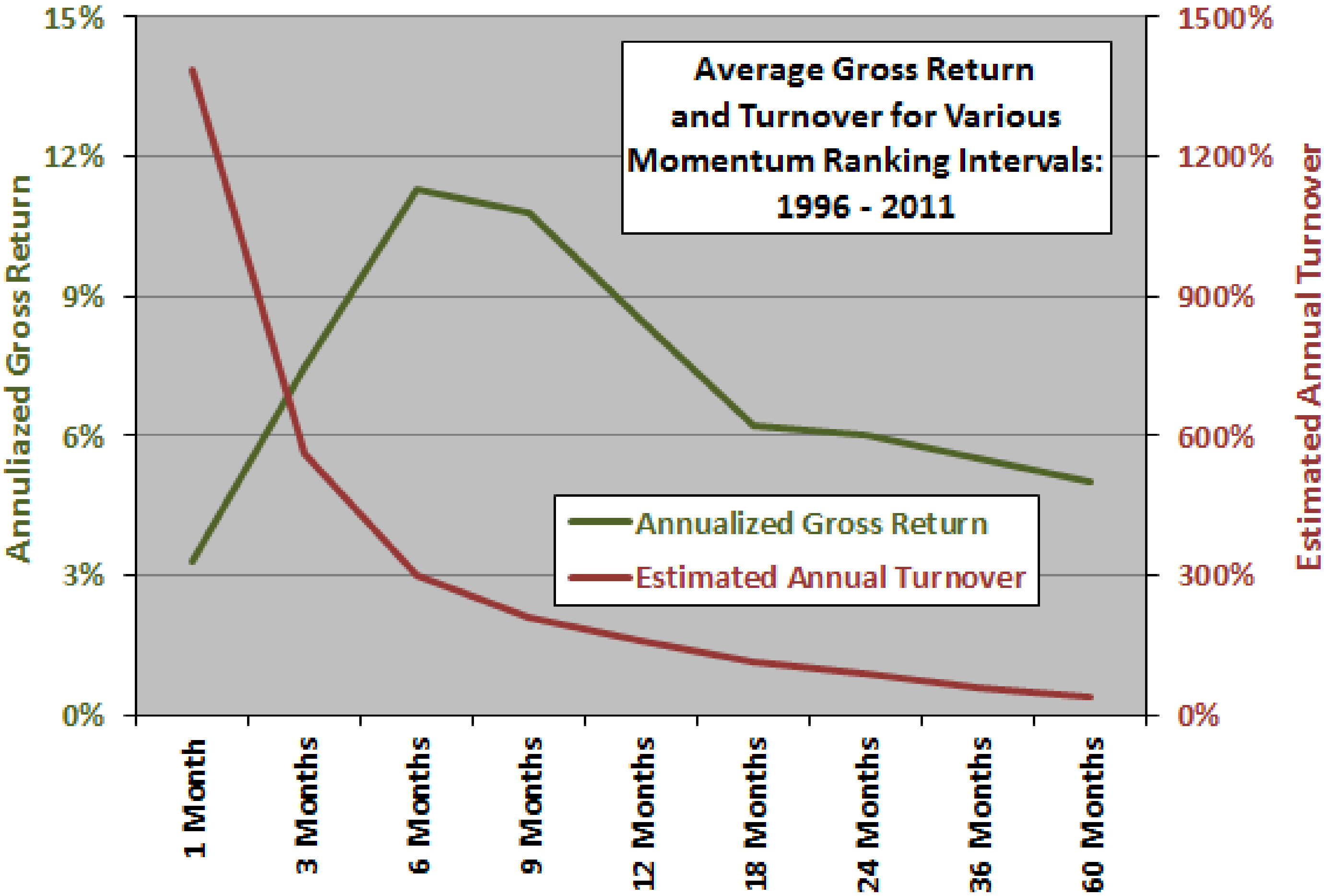
Melding Momentum and Stock Portfolio Management Practices

February 13, 2012

It is arguable that many stock momentum strategy tests derive more from logical/programming simplicity than common portfolio management practices. Does momentum work for portfolios of U.S. stocks when melded with the latter? In the January 2012 update of his paper entitled "Relative Strength and Portfolio Management", John Lewis tests individual stock momentum in the context of real-world stock portfolio practices. After initial selection of top stocks, he replaces weakening stocks with strong ones as needed rather than at a fixed interval, depending on four parameters: (1) momentum ranking interval; (2) number of stocks in the portfolio; (3) buy rank threshold; and, (4) sell rank threshold. To test robustness, he conducts multiple trials based on random selection of stocks above the buy rank threshold. Specifically, he presents nine examples of 100 iterations of 50-stock portfolios randomly selected from the top 10% of the S&P 900 (S&P 500 large-cap plus S&P 400 mid-cap) based on momentum ranking intervals of one month to five years, replacing stocks when they fall out of the top 25%. Portfolios are apparently equally weighted at initial formation. Examples ignore dividends, management fees and trading frictions. Using daily returns (excluding dividends) for the S&P 900 stocks over the period 1996 through 2011 (16 years), *he finds that:*

- For the featured 12-month ranking interval over the entire sample period:
  - Average (median) gross return for the 100 portfolio trials is 271% (257%), compared to a return of 104% for the S&P 500 Index (without dividends).
  - The gross return for the worst trial is 125.9%, still beating the S&P 500 Index.
  - During 1998, 1999, 2005 and 2010 (2006, 2008 and 2009), all (none) of the 100 trial portfolios beat the S&P 500 Index.
- For ranking intervals of three, six, nine and 12 months, all 100 trial portfolios beat the S&P 500 Index over the entire sample period, with average annualized gross returns of 7.5%, 11.3%, 10.8% and 8.5%, respectively, compared to 4.6% for the index.
- Average gross returns for portfolios formed using ranking intervals of one, 18, 24, 36 and 60 months are weaker due to material mean reversion (especially for the one-month ranking interval).
- Turnover escalates as ranking interval decreases, indicating a critical trade-off between responsiveness to trend change and trading friction for ranking intervals in the range of six to 12 months.

The following chart, representative of findings in the paper, compares the annualized average gross return and estimated average annual turnover of the individual stock momentum strategy described above by ranking interval. While a six-month ranking interval maximizes average gross return, a longer ranking interval with lower turnover may maximize average net return.



In summary, *evidence from tests of individual stock momentum in a portfolio management context support belief that ranking intervals in the range six to 12 months outperform the S&P 500 Index over the past 16 years.*

Cautions regarding findings include:

- As noted, return calculations are gross. Including realistic trading frictions would reduce returns materially, perhaps decisively for portfolios of modest value.
- Dividend yield for the top past return decile may tend to be relatively low, making exclusion of dividends from the benchmark advantageous to the momentum strategy.
- The value-weighted S&P 500 Index is arguably not the right benchmark to gauge the intrinsic value of a momentum strategy that weights equally (at least initially) stocks selected from the S&P 900. Equal weighting in itself incorporates a size effect, and momentum winners may skew toward the higher-performing stocks of the S&P 400. The equally weighted, occasionally rebalanced S&P 900 may be stiff competition for the average momentum portfolio. Buying and holding SPY (tracking the S&P 500 Index) and MDY (tracking the S&P 400 Index) with initial equal weights may be competitive. During 1996-2011, dividend-reinvested SPY and MDY generate total returns of 165% and 350%, respectively.

Originally published at http://www.cxoadvisory.com/19607/momentum-investing/melding-

momentum-and-stock-portfolio-management-practices/ on February 13, 2012.

Momentum Investing for Currencies?

January 23, 2012

Does momentum investing work for currencies as it does for equities? In the December 2011 version of their paper entitled "Currency Momentum Strategies", Lukas Menkhoff, Lucio Sarno, Maik Schmeling and Andreas Schrimpf investigate momentum strategies in foreign exchange (FX) markets. FX markets are generally more liquid than equity markets, with huge transaction volumes, low trading frictions and no short-selling constraints. The study's principal analytic approach is to rank 48 currencies monthly based on returns over the past one, three, six, nine and 12 months and use the rankings to form six eight-currency portfolios for holding intervals ranging from one to 60 months. The monthly winners (losers) are the portfolios with the highest (lowest) past returns. Using monthly FX spot and one-month forward price and bid-ask data for 48 currencies relative to the U.S. dollar as available over the period January 1976 through January 2010, *they find that:*

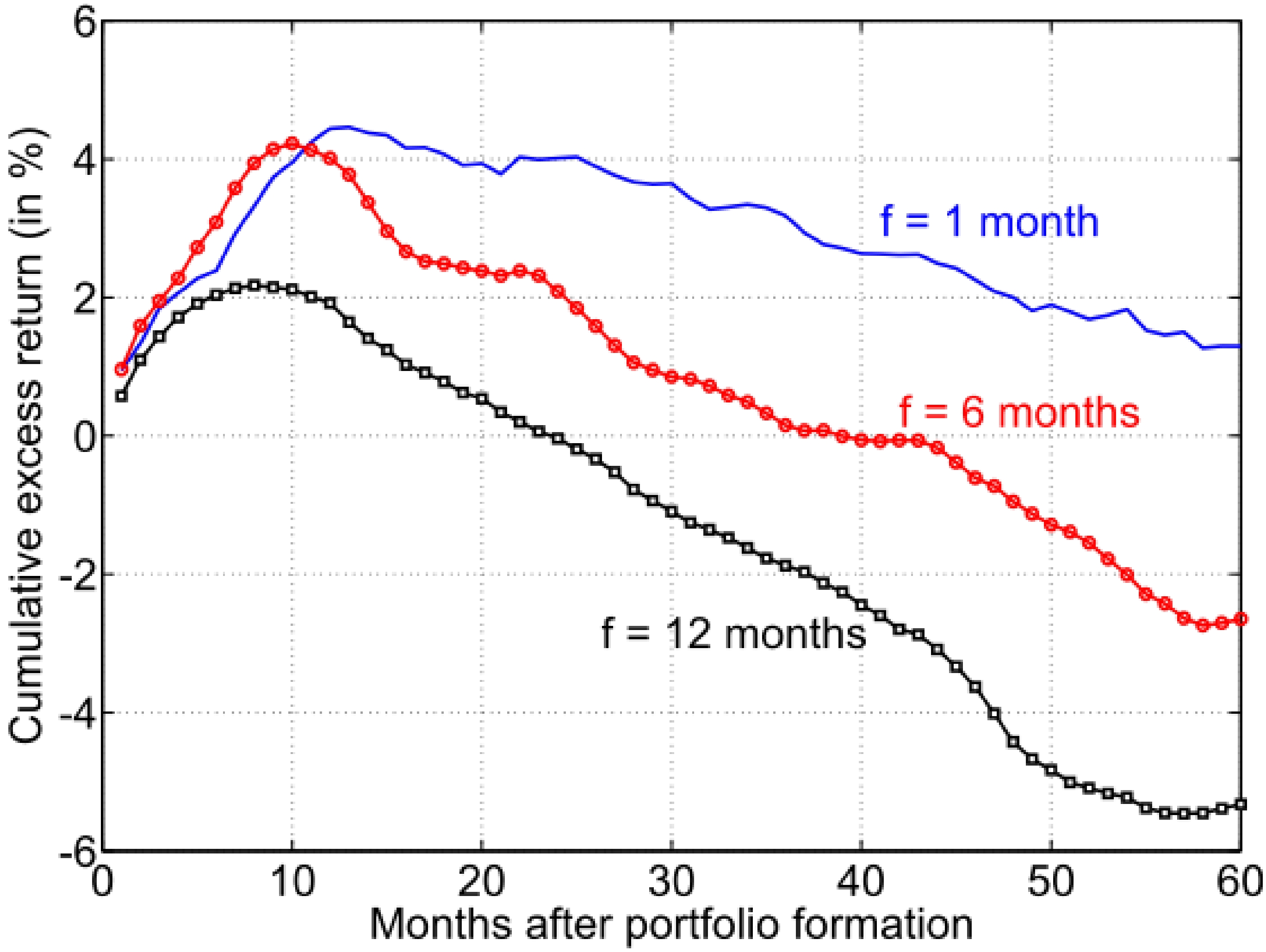
- FX hedge portfolios that are long (short) currency portfolio winners (losers) generate average annualized gross returns of about 6% to 10% for the one-month holding interval. Profitability fades slowly as holding interval increases, with cumulative returns peaking at eight to 12 months and reversing thereafter (see the first chart below).
- FX momentum strategy gross profitability persists after controlling for business cycle, liquidity, carry trade (long high interest rate and short low interest rate currencies) and four equity (market, size, book-to-market, momentum) risk factors.
- FX momentum strategy gross profitability varies considerably over time and with currency characteristics. Gross returns are:
  - Higher for currencies with high rather than low past idiosyncratic volatility (about 8% versus 4% annualized).
  - Higher for currencies with high rather than low risk ratings.
  - Concentrated (half of all profit) in minor currencies with relatively high trading frictions.
- Including trading frictions conservatively based on the full bid-ask spread lowers the average annual profitability of the best FX momentum strategy (one-month ranking and one-month holding intervals) from 10% to 4% and nearly eliminates the profit of many other strategies (see the second chart below). Both high turnover and concentration of gross returns in currencies costly to trade account for this large impact.

The following chart, taken from the paper, shows average cumulative gross returns during the 60 months after portfolio formation for three FX momentum hedge strategies that are long (short) winner (loser) currency portfolios formed monthly on an overlapping basis, as follows:

- f=1 month has a ranking interval of the past month (blue).
- f=6 months has a ranking interval of the past six months (red).

- f=12 months has a ranking interval of the past 12 months (black).

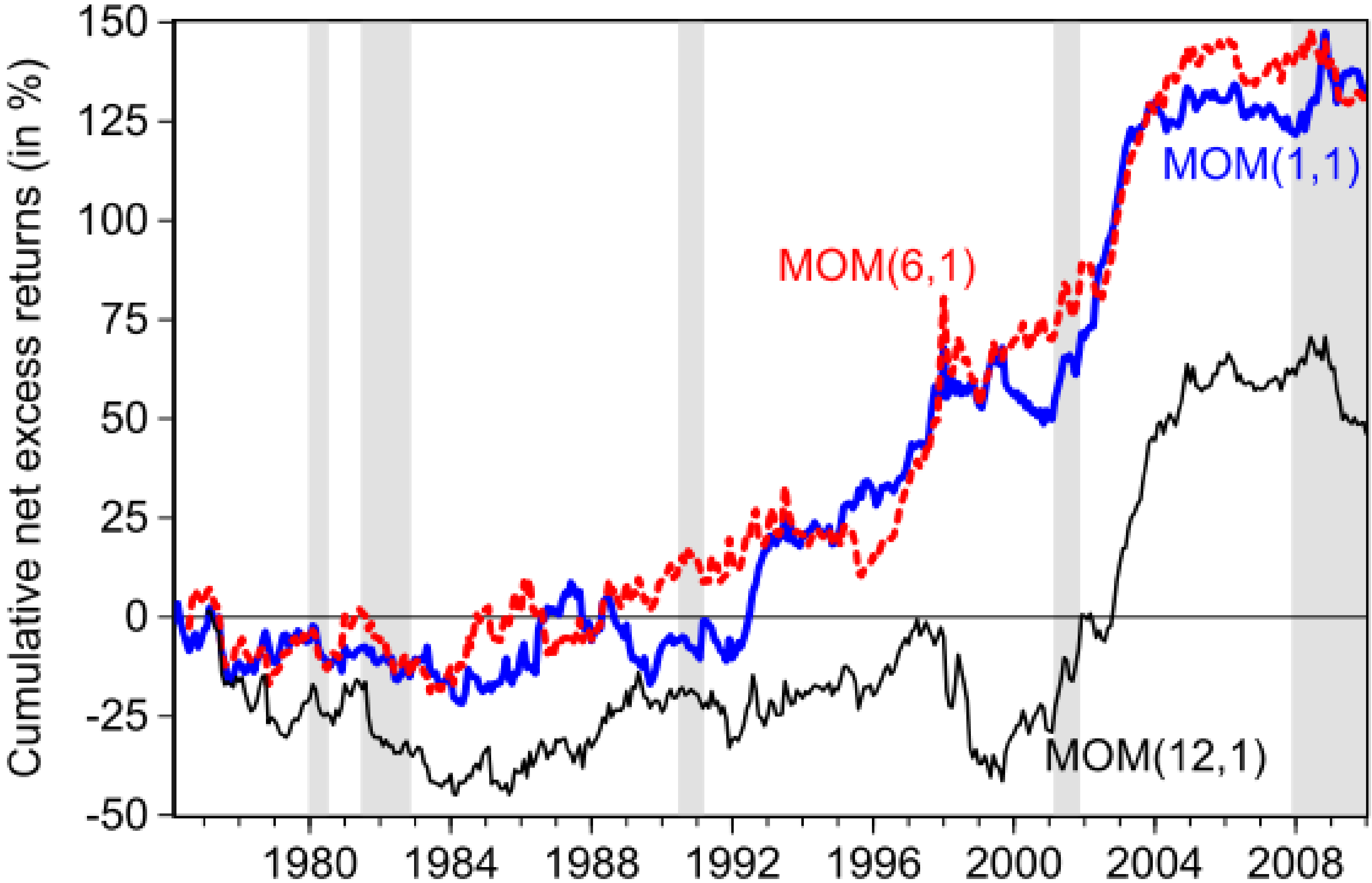
On average, cumulative returns increase most rapidly just after portfolio formation, peak after eight to 12 months and then reverse over longer horizons. Reversal is more pronounced for longer ranking intervals. This pattern suggests a cycle of investor underreaction and overreaction.



The next chart, also from the paper, shows average cumulative net returns for three FX momentum hedge strategies that are long (short) winner (loser) currencies formed monthly on an overlapping basis, as follows:

- MOM (1,1) has a formation interval of one month and a holding interval of one month (blue).
- MOM (6,1) has a formation interval of six months and a holding interval of one month (red).
- MOM (12,1) has a formation interval of 12 months and a holding interval of one month (black).

Trading frictions conservatively include full recorded bid-ask spreads. Shaded areas correspond to NBER recessions (known only retrospectively). Results indicate that FX momentum strategies are much more profitable in the last decade of the sample period and that momentum strategies do not always deliver high returns to investors.



In summary, *evidence indicates that currencies exhibit momentum in a manner similar to that of stocks, but that trading frictions are a substantial barrier to consistent profitability.*

Originally published at http://www.cxoadvisory.com/13612/momentum-investing/momentum-investing-for-currencies/ on January 23, 2012.

Amplifying Momentum with Negatively Correlated Funds?

January 17, 2012

In the brief August 2011 paper entitled "Paired-switching for Tactical Portfolio Allocation", flagged by a subscriber, Akhilesh Maewal and Joel Bock investigate the efficiency of a simple momentum strategy applied to pairs of exchange-traded funds (ETF) with negative return correlations. Every 13 weeks (four times per year), they rank the performances of the two funds over the prior thirteen weeks and buy the fund that has the higher return. They ignore trading frictions. Using weekly adjusted closing levels of SPDR S&P 500 (SPY), iShares Barclays 20+ Year Treas Bond (TLT), iShares MSCI EAFE Index (EFA) and Vanguard Total Stock Market ETF (VTI) over the period from about October 2002 through about June 2011, *they find that:*

- The simple momentum strategy applied to negatively correlated fund pairs generates high returns with low volatility:
  - The SPY/TLT pair (correlation -0.84) generates an annualized gross return of 15.0%, with annual standard deviation 7.6% and worst year 6.7%, far outperforming both SPY and TLT.
  - The EFA/TLT pair (correlation -0.79) generates an annualized gross return of 20.1%, with annual standard deviation 9.5% and worst year 6.2%, far outperforming both EFA and TLT.
  - The VTI/TLT pair (correlation -0.84) generates an annualized gross return of 15.6%, with annual standard deviation 7.6% and worst year 6.9%, far outperforming both VTI and TLT.
- A longer-term test using the Vanguard 500 Index Investor (VFINX) and Vanguard Long-Term Treasury Investor (VUSTX) mutual funds starting in 1991 (correlation -0.21) generates an annualized gross return of 11.3%, with annual standard deviation 9.3% and worst year -11.9%, comfortably outperforming VFINX and VUSTX.
- The strategy substantially improves the performances of "lazy" ETF portfolios such as: 60/40 SPY/TLT since 2003; Andrew Tobias 3-Fund (SPY, EFA, TLT) since 2003; Swensen (0.3 SPY, 0.2 VNQ, 0.2 EFA, 0.3 TLT) since 2005; and Bernstein Basic (SPY, IWB, EFA, TLT) since 2003.
- Since switching frequency is no more than four times per year, trading frictions for a reasonably sized portfolio would be small.
- For some pairs, ranking and holding intervals other than 13 weeks substantially improve results (with attendant data snooping bias).

In summary, *evidence from simple tests suggests that investors may be able to extract high performance from simple momentum strategies by restricting the universe of choices to two assets with very negatively correlated returns.*

Cautions regarding findings include:

- The study apparently uses the same sample to select fund pairs (calculate return correlations) and to measure momentum strategy performance. An investor operating in real time would have only data older than the trading period to select negatively correlated pairs, and pair correlations (such as for stock market and bond market proxies) vary over time. Specifically, an investor may not pick very good pairs for a 2003-2011 momentum strategy test based on correlations from before 2003. This look-ahead bias undermines confidence in findings.
- The number of pairs tested is very small. Repeated tests for many pairs with different (past) return correlations would be needed to confirm a reliable relationship between lagged pair return correlations and future pair switching strategy returns.
- There may be data snooping bias (luck via optimization) in the selection of the 13-week ranking/holding interval.
- As noted in the paper, backtests ignore trading frictions.
- Given the variability of returns, the sample periods are short compared to the ranking interval (27-35 quarterly observations).
- Statistical reliability tests assume tame return distributions.

Originally published at http://www.cxoadvisory.com/18860/momentum-investing/amplifying-momentum-with-negatively-correlated-funds/ on January 17, 2012.

Exploiting Idiosyncratic Volatility in Commodity Futures

January 5, 2012

Can investors exploit idiosyncratic volatility exhibited by commodity futures? In their December 2011 paper entitled "Idiosyncratic Volatility Strategies in Commodity Futures Markets", Adrian Fernancez-Perez, Ana-Maria Fuertes and Joelle Miffre investigate the usefulness of idiosyncratic volatility as a predictor of commodity futures returns. They define idiosyncratic volatility of commodity futures as return volatility not explained by contemporaneous variation in hedging pressure. They calculate hedging pressure from CFTC Commitments of Traders reports by relating long positions to total positions across trader categories. Return calculations assume: (1) holding the first nearby contract up to one month before maturity and then rolling to the next-nearest contract; (2) trading on a fully collateralized basis, meaning that half of trading capital earns the risk-free rate (three-month Treasury bill yield); and, (3) reporting only returns in excess of the risk-free rate, which averages about 3.3% annually over the sample period. They test all combinations of commodity ranking (whether for idiosyncratic volatility, return momentum or roll return) and portfolio holding intervals of 4, 13, 26 and 52 weeks. They calculate alpha by regressing long-short commodity futures portfolio returns against the same-interval hedging pressure risk premium. Using Friday settlement prices of nearest and second-nearest contracts for 27 commodity futures and weekly hedging pressure data during September 30, 1992 through March 25, 2011, *they find that:*

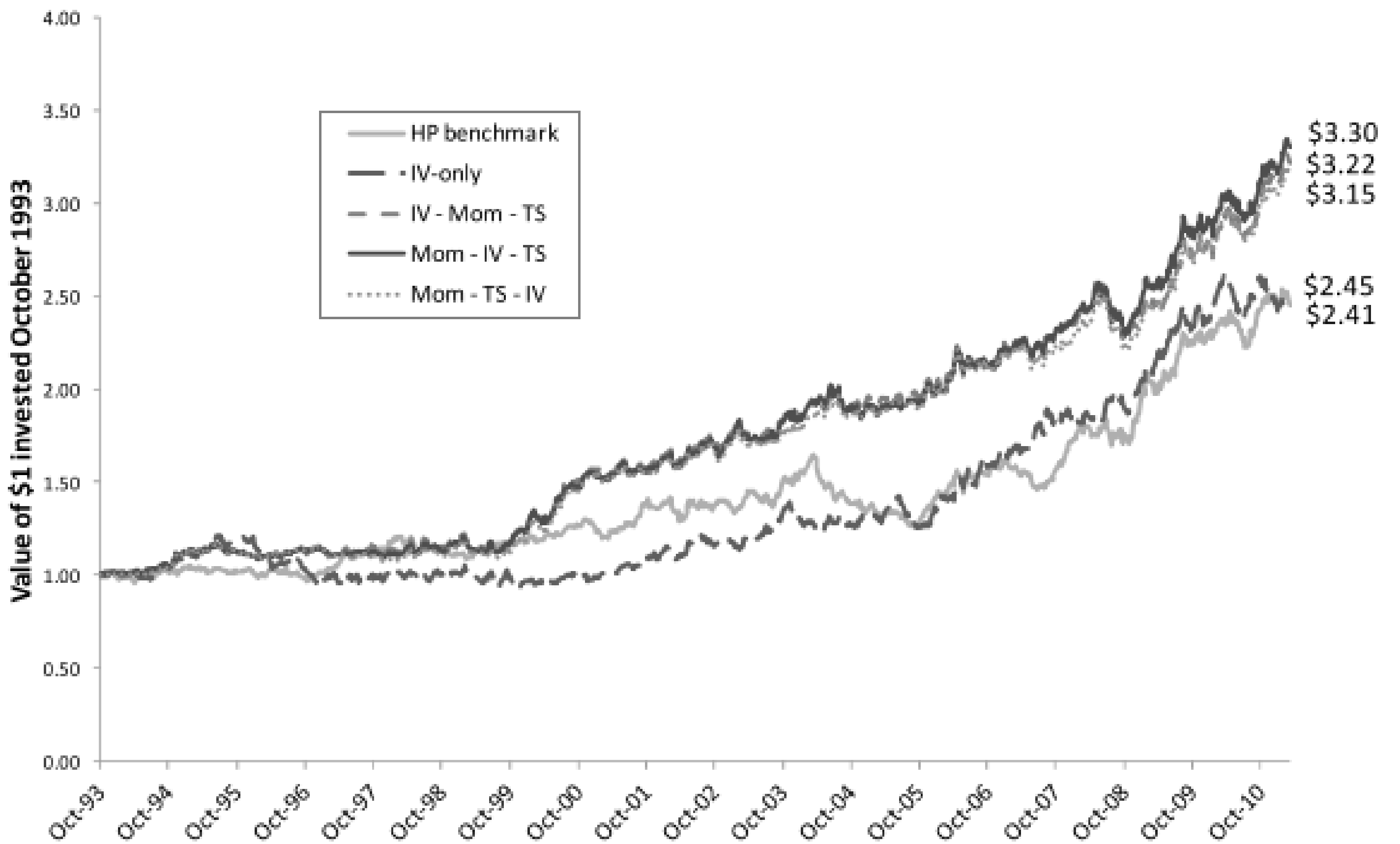
- For a portfolio that is long (short) the equally weighted fifth of commodity futures with the lowest (highest) idiosyncratic volatility:
  - Average annualized gross excess return (alpha) across ranking and holding interval combinations is 5.5% (4.6%).
  - Assuming per-trade friction of 0.033% (0.066%), average annualized net alpha is 4.6% (4.5%), with breakeven per-trade friction about 2.3%.
  - Shorter ranking intervals generally outperform longer ones.
- Idiosyncratic volatility strategies are materially independent of momentum and term structure (roll return) strategies in commodity futures markets.
  - Triple-sort long-short portfolios combining the three anomalies yield an average annualized gross excess return (alpha) of about 7.0% (5.6%) across ranking and holding interval combinations, essentially insensitive to sorting order. Sorting criteria are coarse so that the final long and short sides of the portfolio each contain about a fifth of the 27 contracts.
  - However, triple-sort portfolios underperform single-sort idiosyncratic volatility portfolios during intervals of extremely high and low market volatility.
  - Assuming per-trade friction of 0.033% (0.066%), average annualized net alpha is 4.9% (4.2%) for triple-sort strategies, with breakeven per-trade friction about 0.41%.
- The profitability of idiosyncratic volatility signals survives at some level after accounting

for illiquidity risk, backwardation/contango conditions and correction for data snooping bias.

- While the long-short commodity futures portfolios effectively diversify stocks and bonds, they are less effective as an inflation hedge than long-only commodity indexes.

The following chart, taken from the paper, shows the cumulative gross value of $1 initial investments in five long-short commodity futures portfolios formed from sorting on: hedging pressure (HP benchmark); idiosyncratic volatility (IV-only); and, three triple sorts on idiosyncratic volatility, return momentum (Mom) and term structure/roll return (TS) in different orders.

Results show that an IV-only strategy is competitive with a hedging pressure strategy, and that combining idiosyncratic volatility with momentum and roll return enhances performance.



In summary, *evidence from fairly complicated modeling and multiple tests indicates that traders may be able to exploit unexplained volatility in commodity futures contract returns via a standalone strategy or in combination with momentum and roll return.*

Cautions regarding findings include:

- Data requirements, variable calculations and portfolio construction methods are complicated and likely beyond the reach of many investors (especially individuals). Access for such investors to the strategies tested would therefore entail management and administrative fees.
- Triple sorting a set of just 27 assets is problematic in terms of purifying signals while

maintaining some portfolio diversification.

- Some investors (especially individuals) may not be able to achieve the benchmark levels of trading friction assumed.
- The sample period is short for the longer ranking/holding intervals.

Originally published at http://www.cxoadvisory.com/18423/volatility-effects/exploiting-idiosyncratic-volatility-in-commodity-futures/ on January 5, 2012.

Leveraged Style ETF (2X and -2X) Momentum Strategy

December 30, 2011

A subscriber suggested applying a simple momentum trading strategy to a set of leveraged equity style (size, value-growth) exchanged-traded funds (ETF), including leveraged long and leveraged short counterparts to exploit both positive and negative markets. It seems plausible that leverage may make funds react quickly and strongly to business cycle shifts that affect style performance. However, the costs of maintaining leverage are countervailing. We test a set of 12 ProShares 2X and -2x leveraged sector ETFs, all of which have trading data back at least as far as April 2007:

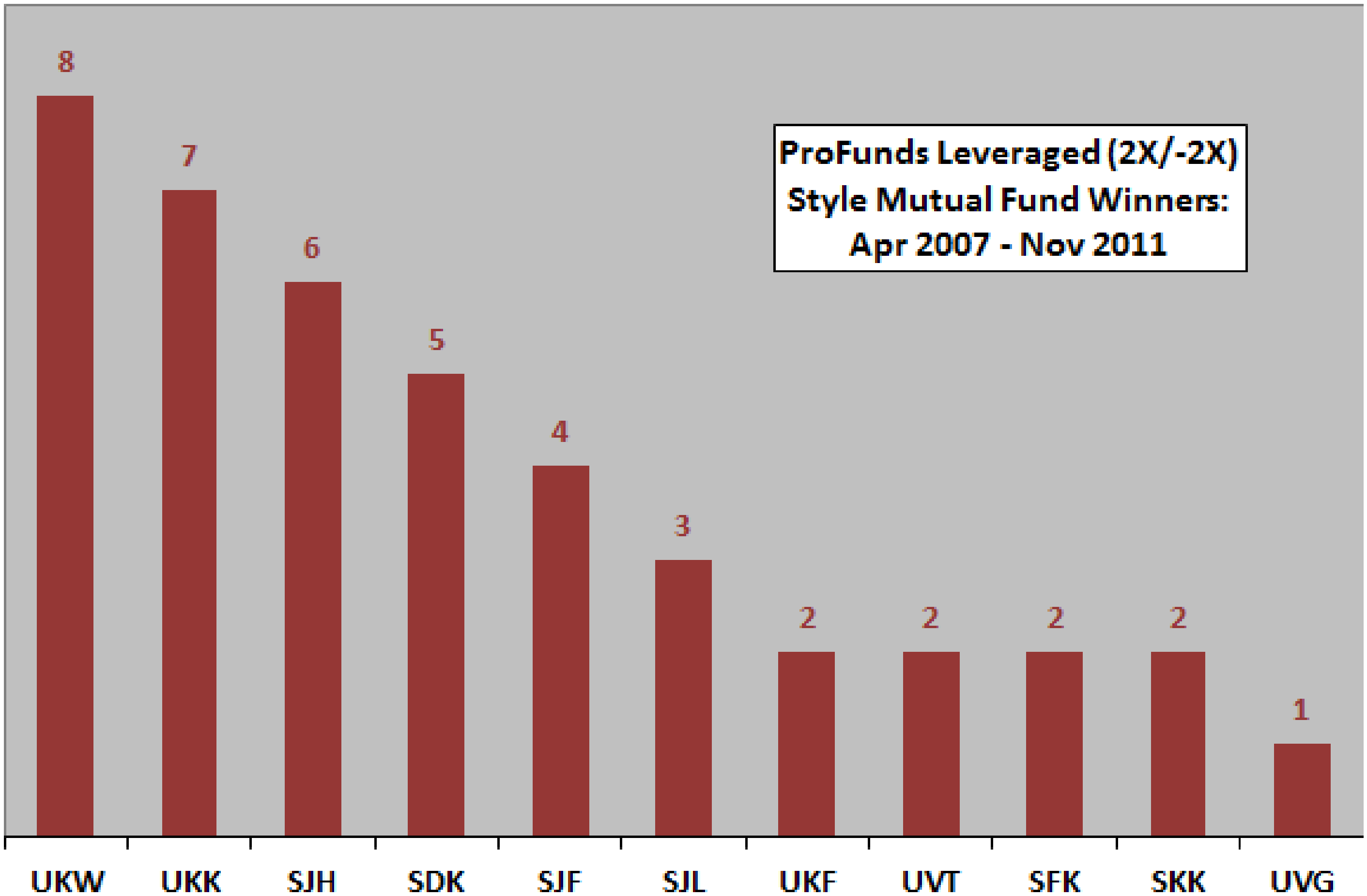
ProShares Ultra Russell1000 Value (UVG)
ProShares Ultra Russell1000 Growth (UKF)
ProShares Ultra Russell MidCap Value (UVU)
ProShares Ultra Russell MidCap Growth (UKW)
ProShares Ultra Russell2000 Value (UVT)
ProShares Ultra Russell2000 Growth (UKK)

ProShares UltraShort Russell1000 Value (SJF)
ProShares UltraShort Russell1000 Growth (SFK)
ProShares UltraShort Russell MidCap Val (SJL)
ProShares UltraShort Russell MCap Growth (SDK)
ProShares UltraShort Russell2000 Value (SJH)
ProShares UltraShort Russell2000 Growth (SKK)

As in "Simple Sector ETF Momentum Strategy Performance" and "Doing Momentum with Style (ETFs)", we consider a basic momentum strategy that allocates all funds at the end of each month to the ETF with the highest total return over the past six months (6-1). Using monthly adjusted closing prices for the 12 leveraged style ETFs and S&P Depository Receipts (SPY) over the period April 2007 through November 2011 (only 56 months), *we find that:*

The following chart shows the distribution of leveraged ETF winners based on past six-month returns over the entire sample period. The mix of 2X and -2X funds obviously depends on broad market bull-bear conditions during the period.

How does applying the 6-1 momentum strategy to these top-ranked ETFs translate into cumulative returns?

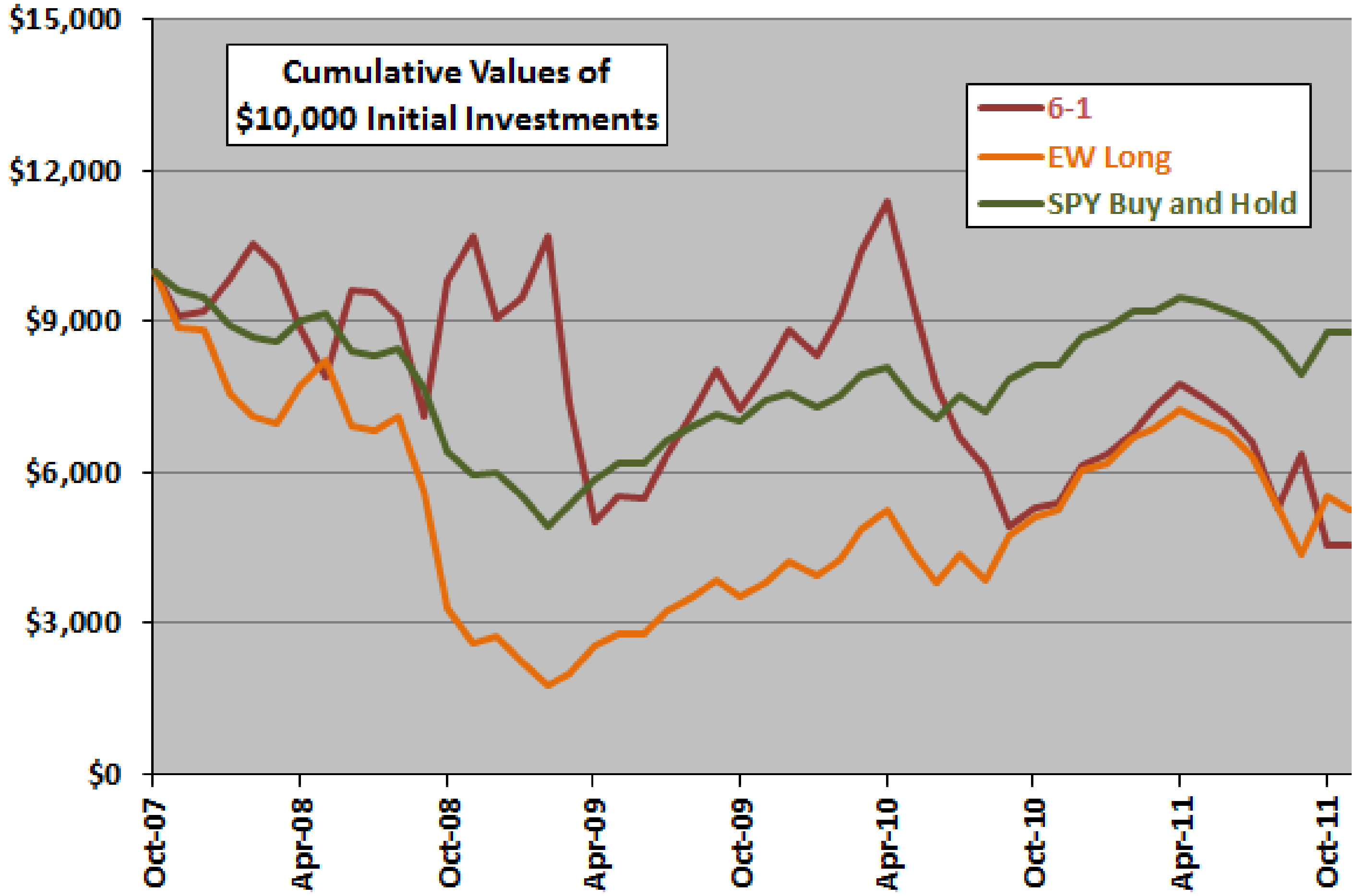


The next chart compares the cumulative values over the sample period of $10,000 initial investments in the leveraged style ETF 6-1 momentum strategy, an equally weighted and monthly rebalanced portfolio of the six 2X style ETFs (EW Long) and buying and holding SPY. Calculations derive from the following assumptions:

- Reallocate at the close on the last trading day of each month (assume we can estimate six-month past total returns for the ETFs just before the concurrent close).
- Ignore trading frictions.
- Ignore any tax implications of trading.

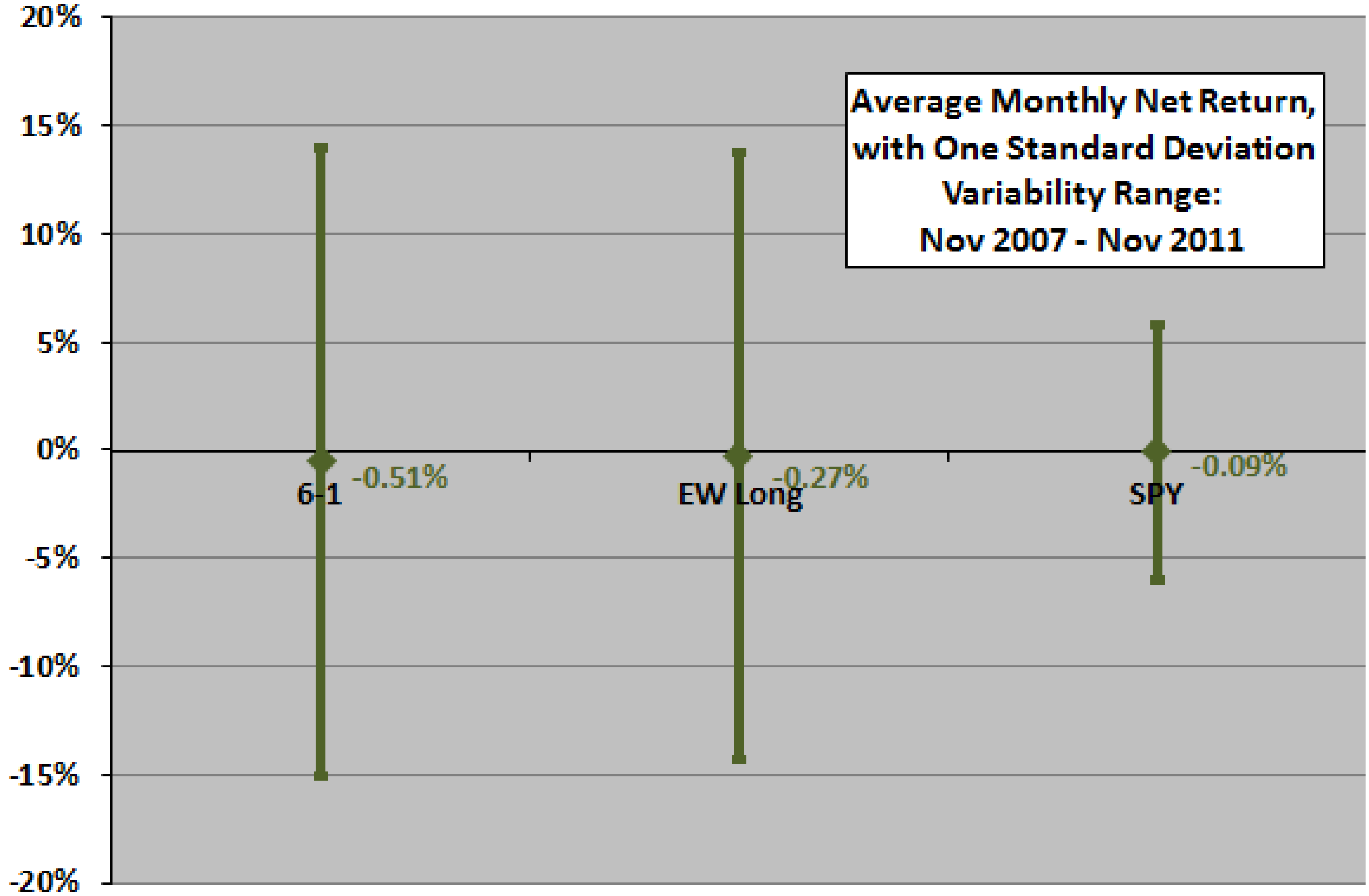
On a frictionless trading basis, the 6-1 momentum strategy sometimes outperforms and sometimes underperforms buying and holding SPY. Both the 6-1 momentum strategy and the EW Long benchmark have lower terminal values than SPY, with much more volatility.

How do average monthly returns, as alternative measures of strategy performance, compare?



The final chart depicts average monthly returns and standard deviations of monthly returns for the leveraged style ETF 6-1 momentum strategy, EW Long and buying and holding SPY over the entire sample period. Even on a frictionless trading basis, SPY buy-and-hold has the highest (though still negative) average monthly return and by far the lowest monthly volatility.

The average monthly return for the 6-1 strategy when operating on 2X (-2X) fund signals is +0.90% (-2.39%), indicating that the short side does not work.



In summary, *evidence from simple tests over a very short sample period do not support belief that a basic leveraged style ETF (2X and -2X) momentum strategy is attractive.*

Cautions regarding findings include:

- As noted, sample size is very small (fewer than ten independent six-month momentum ranking intervals).
- Including trading frictions would lower the performance of the 6-1 momentum strategy and the EW Long benchmark.
- Ranking intervals other than six months and holding periods other than one month may produce different results. Optimizing the ranking and holding intervals would impound data snooping bias,
- Lengthy holding periods for leveraged funds are problematic (see "Multi-year Performance of Leveraged ETFs" as linked above, plus "Multi-year Performance of Non-equity Leveraged ETFs", "Unintended Characteristics of Leveraged and Inverse ETFs" and "Performance of Leveraged ETFs over Extended Holding Periods").
- Potential wildness in leveraged ETF monthly return distributions further limits confidence in results.

Originally published at http://www.cxoadvisory.com/18462/volatility-effects/leveraged-style-etf-2x-and-2x-momentum-strategy/ on December 30, 2011.

Leveraged Sector Fund Momentum Strategy

December 22, 2011

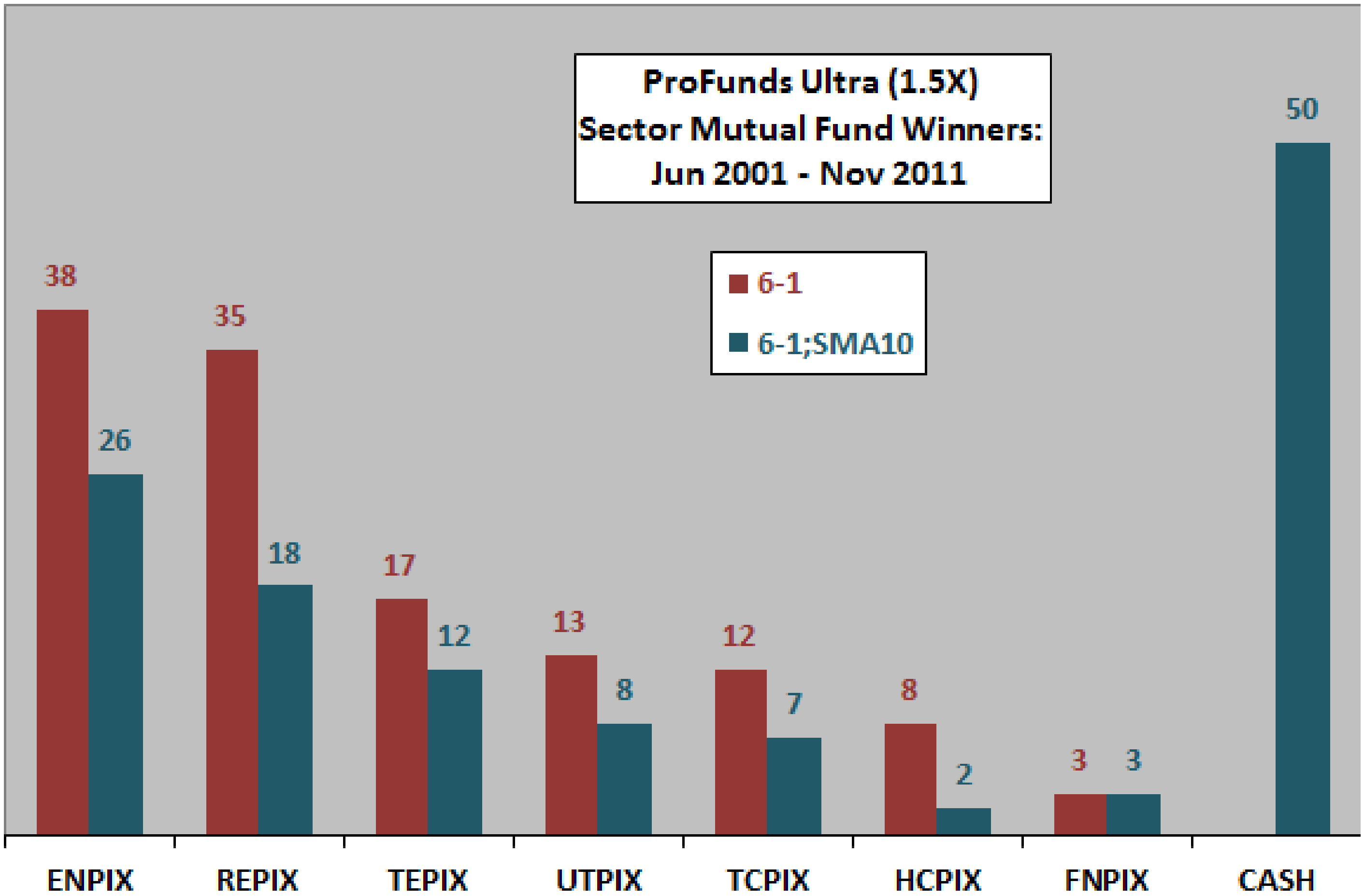
A subscriber suggested applying simple momentum trading strategies to a set of leveraged equity style (size, value-growth) funds. It seems plausible that leverage may make funds react quickly and strongly to business cycle shifts that affect style performance. However, the costs of maintaining leverage are countervailing. Historical data for leveraged style funds is very limited, so we test instead a set of seven ProFunds 1.5X leveraged sector mutual funds, all of which have trading data back at least as far as December 2000:

ProFunds UltraSector Oil & Gas Inv (ENPIX)
ProFunds UltraSector Financials Inv (FNPIX)
ProFunds UltraSector Health Care Inv (HCPIX)
ProFunds Real Estate UltraSector Inv (REPIX)
ProFunds Telecom UltraSector Inv (TCPIX)
ProFunds Technology UltraSector Inv (TEPIX)
ProFunds Utilities UltraSector Inv (UTPIX)

As in "Simple Sector ETF Momentum Strategy Performance" and "Doing Momentum with Style (ETFs)", we consider a basic momentum strategy that allocates all funds at the end of each month to the mutual fund with the highest total return over the past six months (6-1). We also consider a more cautious strategy that allocates all funds at the end of each month either to the mutual fund with the highest total return over the past six months or to cash depending on whether the S&P 500 Index is above or below its 10-month simple moving average (6-1; SMA10). Using monthly adjusted closing prices for the seven leveraged sector funds, the S&P 500 index, 3-month Treasury bills (T-bills) and S&P Depository Receipts (SPY) over the period December 2000 through November 2011 (132 months), *we find that:*

The following chart shows the distribution of leveraged sector mutual fund winners based on past six-month total return over the entire sample period for both the 6-1 and 6-1;SMA10 momentum strategies. For the latter, the strategy is in cash 38% of the time.

How does applying the strategies to these top-ranked funds translate into cumulative returns?

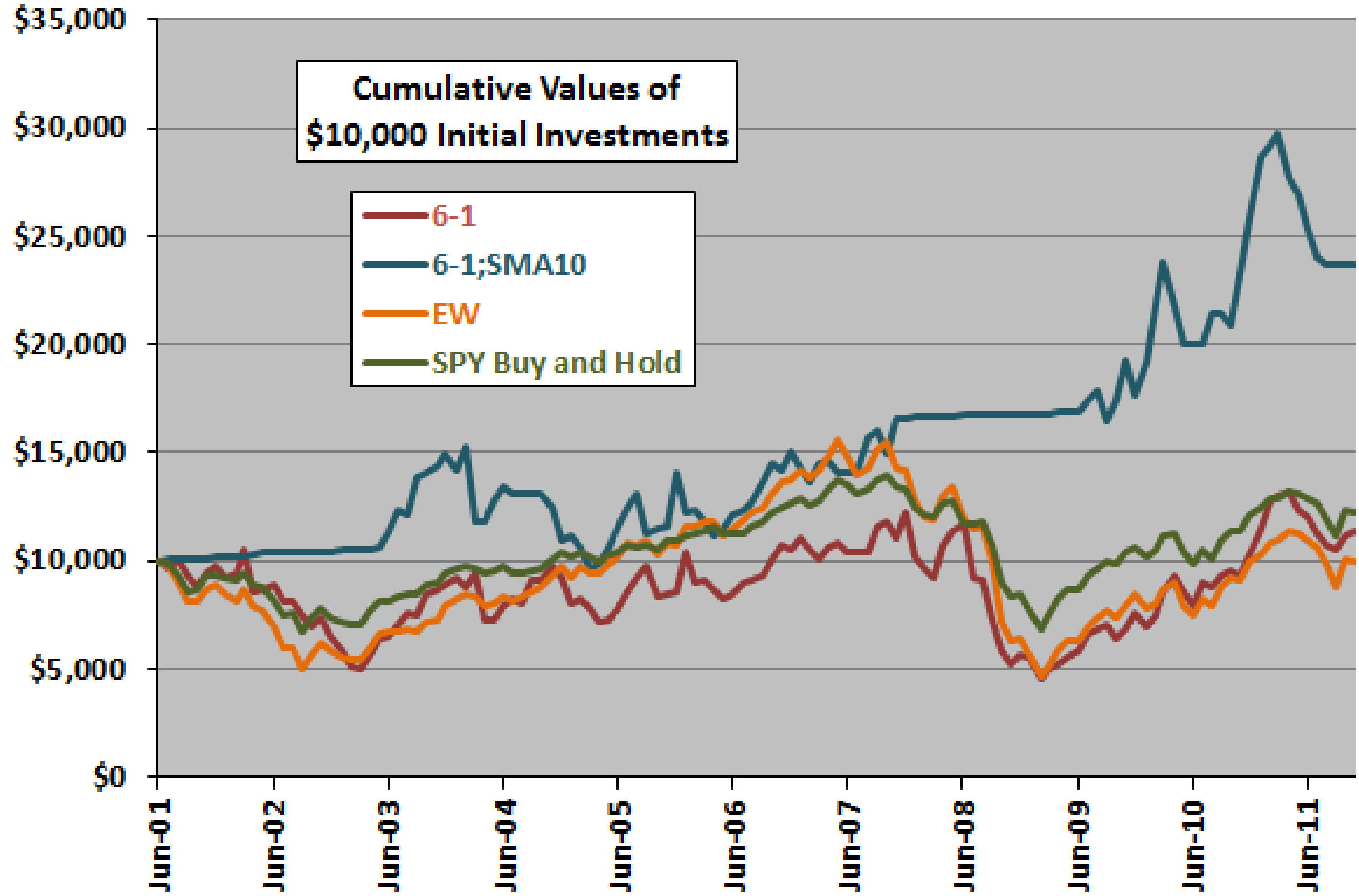


The next chart compares the cumulative values over the sample period of $10,000 initial investments in: the two leveraged sector mutual fund momentum strategies; an equally weighted and monthly rebalanced portfolio of the seven mutual funds (EW); and, SPY. Calculations derive from the following assumptions:

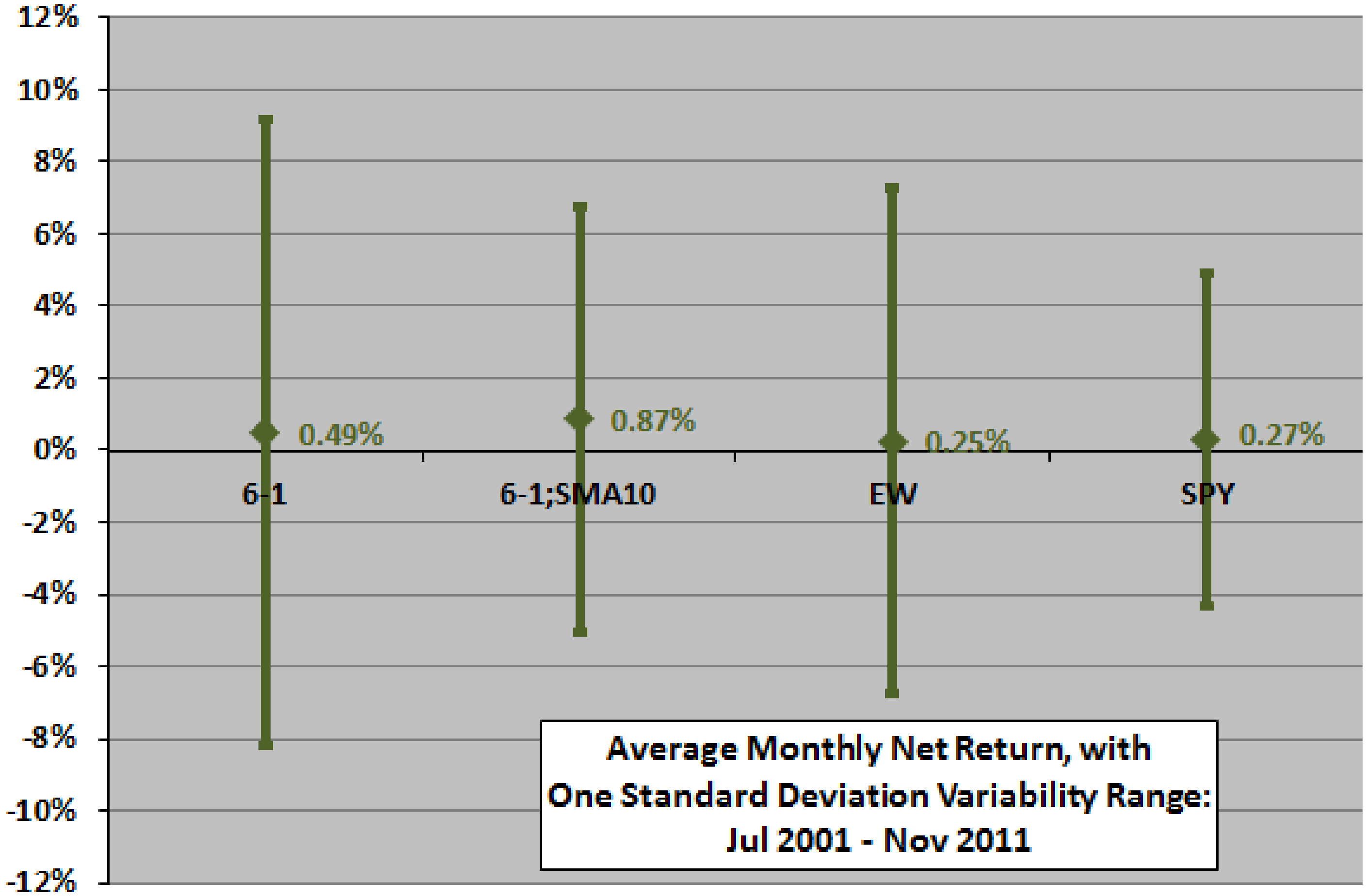
- Reallocate at the close on the last trading day of each month (assume we can estimate six-month past total returns for the mutual funds based on prior-day closes and S&P 500 Index SMA crossing signals just before the concurrent close).
- Per the ProFunds fund exchange policy, there are no trading frictions.
- Return on cash for the 6-1;SMA10 variation is equal to the T-bill yield at the time of allocation.
- Ignore any tax implications of trading.

The 6-1 momentum strategy mostly underperforms buying and holding SPY and is no better than an equal-weighted portfolio of the seven funds (EW). The 6-1;SMA10 strategy generally outperforms SPY by avoiding major market downturns. The 6-1;SMA10 strategy less consistently outperforms a simple strategy of investing in SPY or cash according to the SMA10 signal (not shown).

How do average monthly returns, as alternative measures of strategy performance, compare?



The final chart depicts average monthly returns and standard deviations of monthly returns for the two leveraged sector mutual fund momentum strategies, an equal-weighted portfolio of the funds and buying and holding SPY over the entire sample period. The 6-1;SMA10 variation has the highest average monthly return with relatively low volatility (because of frequent allocation to cash).



In summary, *evidence from simple tests indicates that a basic leveraged sector mutual fund momentum strategy has mostly underperformed the broad stock market over the past 13 years. Combining such a strategy with a simple moving average signal for entering and exiting stocks may be attractive.*

Cautions regarding findings include:

- Sample size is modest (just 22 independent six-month momentum ranking intervals and only 13 independent 10-month SMA intervals).
- The assumption of concurrent momentum measurements and trading is riskier for mutual funds than exchange-traded funds because prices for the former are available only for the close.
- The selected fund ranking interval derives from prior academic studies. This prior research may impound (and therefore transmit) data snooping bias, which is especially pernicious for small samples. Ranking intervals other than six months and holding periods other than one month may produce different results. Optimizing the ranking and holding intervals would elevate data snooping bias.
- Lengthy holding periods for leveraged funds are problematic (see "Multi-year Performance of Leveraged ETFs" as linked above, plus "Multi-year Performance of Non-equity Leveraged ETFs", "Unintended Characteristics of Leveraged and Inverse ETFs" and "Performance of Leveraged ETFs over Extended Holding Periods"). Using funds with leverage higher than 1.5X may change results, perhaps detrimentally for a simple momentum strategy but possibly advantageously in combination with an SMA rule.

- Including more sector/asset class funds may enhance results, but also may not.
- Potential wildness in leveraged fund monthly return distributions limits confidence in results.

Originally published at http://www.cxoadvisory.com/18347/volatility-effects/leveraged-sector-fund-momentum-strategy/ on December 22, 2011.

The 2000s: A Market Timer's Decade?

December 2, 2011

Do the poor returns and high volatility of the "buy-and-hold-is-dead" U.S. stock market since the beginning of 2000 represent a tailwind for market timers? In other words, is buy-and-hold effective as a benchmark for distinguishing between market timer luck and skill in recent years? To check, we measure the performances of various simple monthly market timing approaches (equal weighting with cash, 10-month simple moving average signals, momentum, and coin-flipping) during the 2000s. Using monthly closes for the dividend-adjusted S&P 500 Depository Receipts (SPY), the 3-month Treasury bill (T-bill) yield and the S&P 500 Index from December 1999 through October 2011 (earlier for S&P 500 Index signal calculations), *we find that:*

The following table summarizes S&P 500 Index monthly return statistics for January 1950 through December 1999 and January 2000 through October 2011. The arithmetic mean monthly return is much lower, and the standard deviation of monthly returns higher, since the beginning of 2000 than during the prior half-century. The percentage of months with positive returns is lower.

S&P 500 Index Monthly	Mean Return	Standard Deviation	% Positive Months
1950-1999	0.83%	4.07%	60%
2000-2011	0.14%	4.73%	55%

Consider a fly-off of the following simple long-only strategies during the 2000s:

1. Buy and Hold: Buy and hold SPY (as a benchmark).
2. EW SPY-Cash: Hold equal amounts of SPY and cash, rebalancing monthly.
3. 10-Month SMA: Hold SPY (cash) when the monthly close of the S&P 500 Index is above (below) its 10-month simple moving average (SMA).
4. 6-1 Intrinsic Momentum: Hold SPY (cash) when the past 6-month return for the S&P 500 Index is positive (negative).
5. 6-1-1 Intrinsic Momentum: Hold SPY (cash) when the past 6-month return, with a skip-month, for the S&P 500 Index is positive (negative).
6. 100 Monthly Coin Flippers: Hold SPY (cash) when the coin comes up heads (tails). Note that, after a large number of trials, the average performance of coin flippers will approximately match EW-SPY-Cash.

For this fly-off, we make the following assumptions:

- The return on cash is the 3-month T-bill yield (divided by 12).
- There are no trading frictions (biased in favor of all timing strategies). The effect of actual

trading frictions depend on strategy trading frequency, bid-ask spread, specific broker fees and account size.
- For the 10-Month SMA and 6-1 Momentum strategies, signals derive from data just before monthly closes, allowing executions at monthly closes.
- Ignore tax implications of trading.

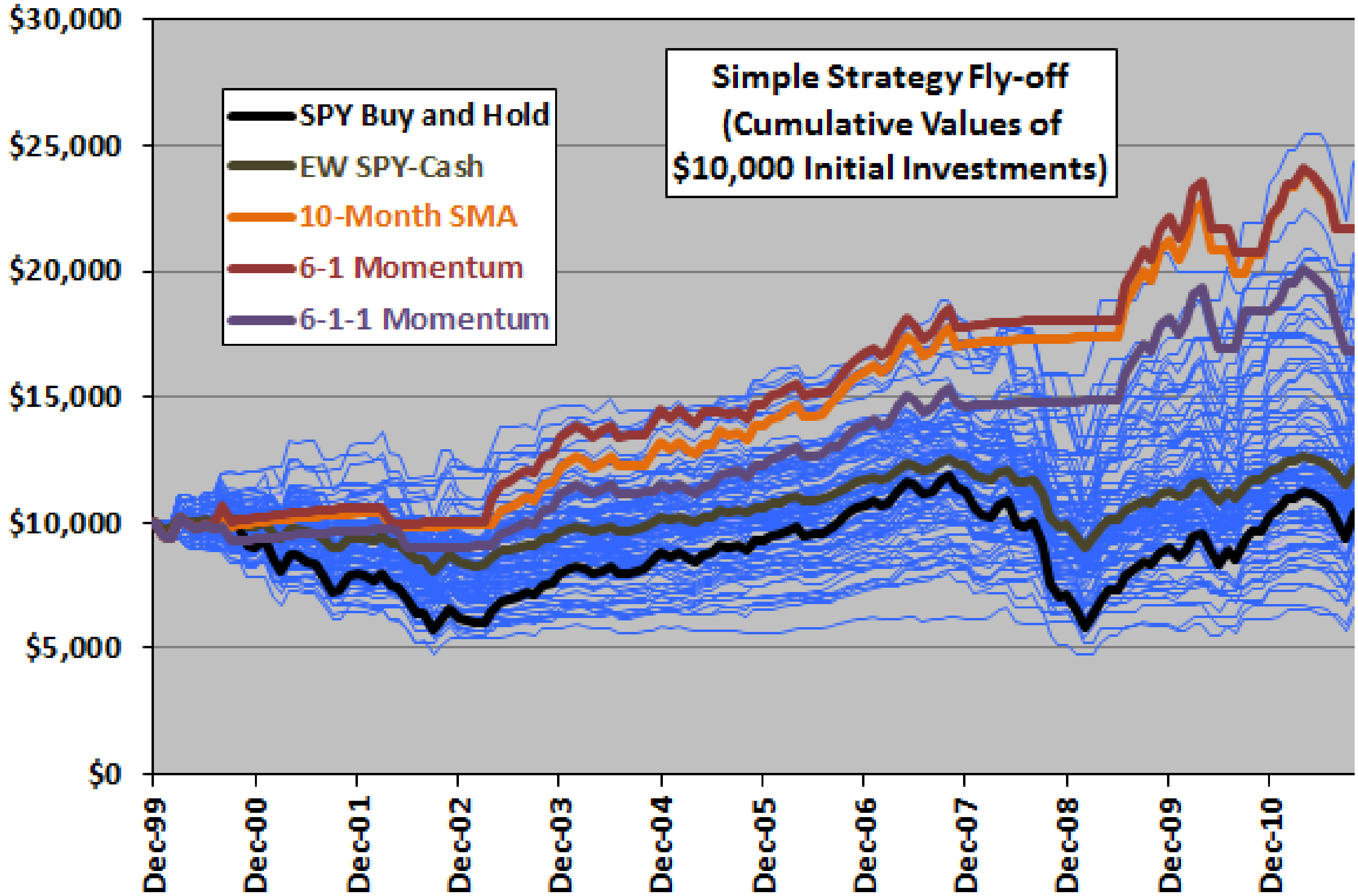
The following chart compares the gross cumulative performances of the above strategies during January 2000 through October 2011, tracking the 100 coin flippers with thin blue lines and the other strategies with thick lines. Some notable findings, based on gross terminal values, are:

- 72% of Monthly Coin Flippers beat Buy and Hold, and the average Monthly Coin Flipper beat the market by 19%. In other words, the sample period presents a tailwind for long-only market timers.
- The best (worst) Monthly Coin Flipper outperformed (underperformed) Buy and Hold by 133% (-39%).
- The 10-Month SMA and 6-1 Momentum strategies perform very similarly and beat all but one of the 100 Monthly Coin Flippers. Either these two strategies add value, or they are very lucky within this sample.

As expected, because it is half out of the market, the EW SPY-Cash strategy generates a gross cumulative return evolution very similar to that of the average Monthly Coin Flipper (not shown).

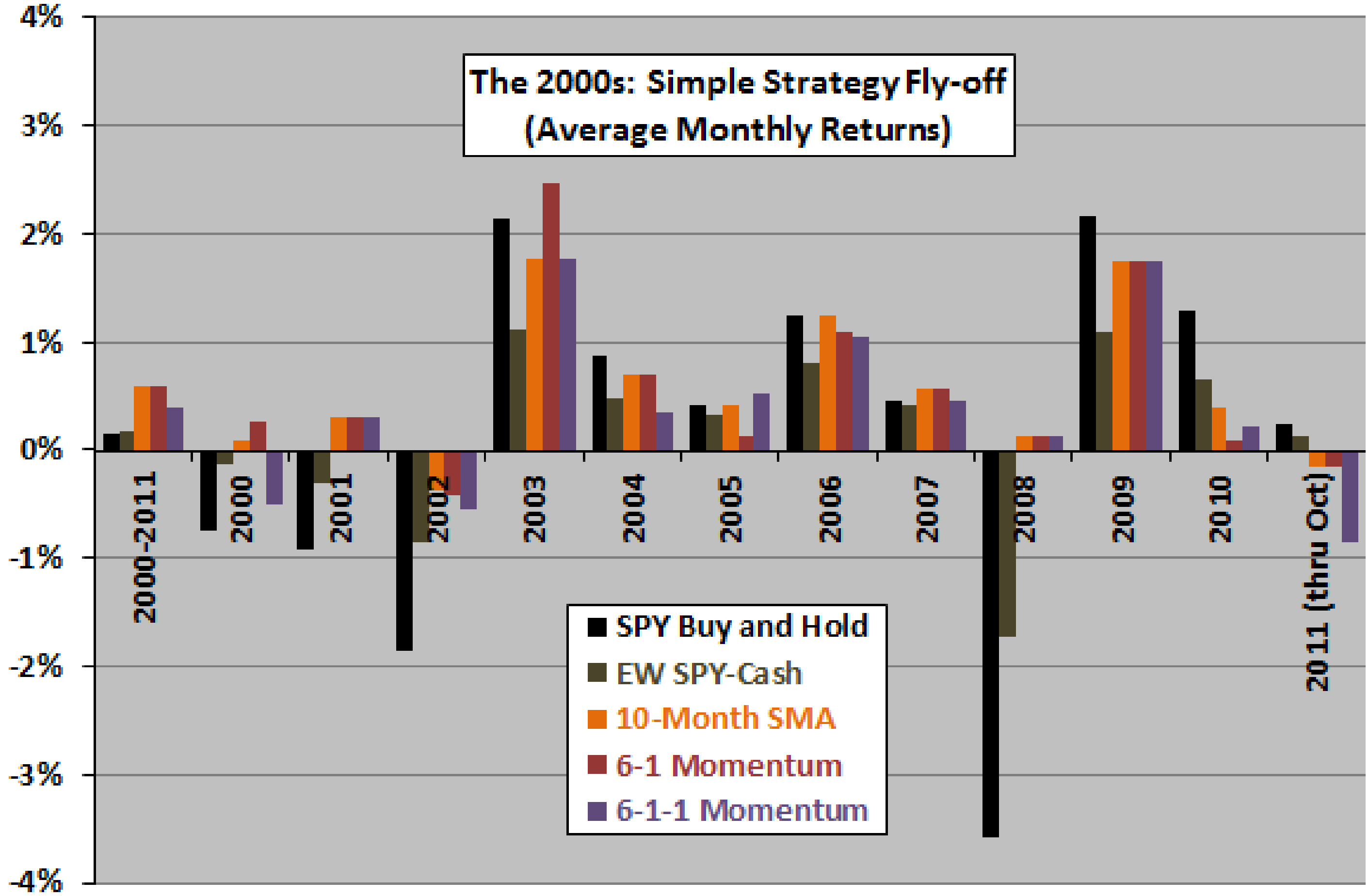
Imposing trading frictions would depress results for all timing strategies (by differing amounts according to trading frequency).

For a different view, we look at average monthly returns.



The next chart compares the average (arithmetic mean) gross monthly returns for the above strategies during January 2000 through October 2011 and during each year over this period. As noted above, the average performance of the Monthly Coin Flippers is similar to that for EW SPY-Cash.

The EW SPY-Cash, 10-Month SMA, 6-1 Momentum and 6-1-1 Momentum strategies have similarly low standard deviations of monthly returns compared to Buy and Hold. Standard deviations of monthly returns for the Monthly Coin Flippers are lower than those for Buy and Hold but higher than the low-volatility strategies.



In summary, *long-only timers of the U.S. stock market who did not beat the market during 2000-2011 have some explaining to do. Even those timers whose signals add no value were likely to beat the market at a gross level.*

Cautions regarding findings include:

- As noted, reported returns are gross. Including reasonable trading frictions would reduce returns for all the strategies that involve trading/rebalancing and could change their relative performance for some investors.
- 100 trials is not a lot for this type of test. Repeating with 100 new trials may generate noticeably different statistics for the Monthly Coin Flippers.
- 12 years is a short sample period for testing signals with signal measurement intervals of six and ten months.
- Performance of signal-based strategies may be sensitive to the assumption of coincident month-end measurement and execution.

Originally published at http://www.cxoadvisory.com/4484/big-ideas/the-2000s-a-market-timers-decade/ on December 2, 2011.

Momentum Echo Outside the U.S.?

November 30, 2011

Research on the U.S. equity market indicates that "old" or intermediate momentum (12 months ago to 7 months ago) is much more important than "new" or recent momentum (6 months ago to two months ago, incorporating a skip-month to avoid short-term reversal) in predicting future stock returns. Do other equity markets confirm this finding? In their September 2011 preliminary paper entitled "Is Momentum an Echo?", Amit Goyal and Sunil Wahal investigate whether other country equity markets behave similarly. Using regressions, single-sorts on past stock returns and double-sorts on intermediate and recent past stock returns, along with country-specific risk factors (market, size, book-to-market), for 36 non-U.S. country equity markets during 1991 through 2009, *they find that:*

- Regression tests across country markets over the sample period indicate that:
  - The value premium (based on book-to-market ratio) is consistently strong.
  - The size effect is relatively weak.
  - Prior-month return relates negatively to next-month return (short-term reversal).
  - In markets with strong momentum effects, both intermediate and recent returns relate positively to next-month return, but the strength of the two relationships is not statistically different in 35 of 36 markets. In the one market for which the difference is significant (UK), recent past returns are more predictive than intermediate past returns.
- For value-weighted winner-minus-loser single-sort momentum portfolios:
  - None of 16 emerging markets exhibit a reliable difference in future returns between portfolios formed on "old" or "new" momentum.
  - Two of 20 developed markets (UK and Sweden) exhibit differences, but in both cases recent past returns are more effective than intermediate past returns.
- For value-weighted intermediate winner-minus-loser and recent winner-minus-loser double-sort momentum portfolios:
  - In most countries, spreads between extreme double-sorted portfolios based on intermediate versus recent momentum are small and highly volatile.
  - In places where the spreads are large, they generally indicate that "new" momentum is more important than "old" momentum. For example, the average monthly gross return of the UK winner-minus-loser portfolio based on intermediate (recent) momentum among stocks in the recent (intermediate) loser portfolio is 0.76% (1.38%).
- Randomness is a possible explanation for the unusual U.S. results in the original research. If differences between intermediate and recent momentum portfolio returns are normally distributed across country markets with zero mean and some variance, one or two false positives are very likely.

In summary, *evidence from multiple tests applied to monthly returns for 36 non-U.S. equity markets does* *not* *support a general belief that "old" momentum is more important than "new" momentum in predicting future stock returns.*

Cautions regarding findings include:

- Returns presented are gross, not net, and monthly momentum strategies tend to have high turnover. Including reasonable estimated trading frictions would materially reduce these returns.
- Moreover, trading frictions may vary considerably across markets and types of stocks, such that findings based on estimated net returns may differ from those based on gross returns.
- Statistical significance tests assume well-behaved distributions. Wildness in distributions would undermine validity of the tests.

Originally published at http://www.cxoadvisory.com/17834/momentum-investing/momentum-echo-outside-the-u-s/ on November 30, 2011.

A Few Notes on What Works on Wall Street

November 25, 2011

James O'Shaughnessy (Chairman and CEO of O'Shaughnessy Asset Management) introduces his 2011 book, *What Works on Wall Street (Fourth Edition): the Classic Guide to the Best-Performing Investment Strategies of All Time*, by stating: "…investors seem programmed by nature to fail at investing, forever chasing the asset class that has turned in the best performance recently and heavily discounting *anything* that occurred more than three to five years ago. The whole purpose of *What Works on Wall Street* is to dissuade investors from that course of action. Only the fullness of time shows which investment strategies are the best long-term performers, and this is doubly true after the last decade's sorry performance. …We will make the case that equities–particularly those selected using the best long-term strategies–will go on to be the best performing assets over the next 10 and 20 years. …The fourth edition of What Works on Wall Street continues to offer readers access to long-term studies of Wall Street's most effective investment strategies." He uses overlapping portfolios formed monthly and rebalanced annually for all tests. Using broad sets of data on U.S. firms/stocks from either 1963 or 1926 through 2009 to extend and expand his prior quantitative analyses, *he concludes that:*

> From Chapter 1, "Stock Investment Strategies: Different Methods, Similar Goals" (Page 4): "…all strategies have performance cycles in which they over- and underperform their relevant benchmarks. The key to outstanding long-term performance is to find strategies that have the highest base rate [frequency with which they beat their benchmark]…and then stick with that strategy, even when it's underperforming other strategies and benchmarks."
>
> From Chapter 2, "The Unreliable Experts: Getting in the Way of Outstanding Performance" (Page 21): "The most ironclad rule I have been able to find studying masses of data on the stock market…is the idea of reversion to the mean. …The same holds true at the strategy level."
>
> From Chapter 3, "The Persistence of Irrationality: How Common Mistakes Create Tremendous Opportunity" (Page 40): "To break from our all too human tendencies to avoid losses even when it is disadvantageous to do so, chase performance, and perceive patterns where there are none, we must find an investment strategy that removes subjective, human decision making from the process and relies instead on smart, empirically proven systematic strategies. …we can become wise by realizing just how unwise we truly are."
>
> From Chapter 4, "Rules of the Game" (Pages 45, 59): "My goal in this book is to bring a more methodical, scientific method to stock market decisions and portfolio construction. To

do this, I have tried to stay true to those scientific rules that distinguish a method from a less rigorous model. …Transaction costs and bid/ask spreads are not included. Each reader faces different transaction costs. …you should subtract as much as 1 percent of gains [to account for bid/ask spreads]…for the data from the 1960s through the 1980s… Currently, our traders at O'Shaughnessy Capital Management have found that bid/ask spreads on small-cap trades average 0.50 percent and 0.15 percent on large-cap trades."

Chapters 5 through 15 and 17 through 20 examine the historical performance of 16 firm characteristics: market capitalization, price-to-earnings ratio, EBITDA to enterprise value, price-to-cash flow ratio, price-to-sales ratio, price-to-book value, dividend yield, buyback yield, shareholder yield (dividend plus buyback), accounting ratios, composite value factor, one-year earnings per share percentage change, profit margin, return on equity, and relative price strength (momentum).

From Chapter 16, "The Value of Value Factors" (Page 355): "Value strategies work, rewarding patient investors who stick with them through bull and bear markets and through bubble and burst."

From Chapter 21, "Using Multifactor Models to Improve Performance" (Page 470): "…you can do *vastly* better than a passive investment…by using more than one factor to select a portfolio of stocks. …Investors are best served by buying stocks that have jumped a series of hurdles rather than just one."

From Chapter 22, "Dissecting the Market Leaders Universe: The Ratios That Add the Most Value" (Page 484): "…focusing on the most expensive popular stocks delivers the worst overall returns, while concentrating on the cheapest stocks delivers the best returns. In addition, the strategies that provided the best overall compound returns also did so with the highest degree of consistency."

From Chapter 23, "Dissecting the Small Stocks Universe: The Ratios That Add the Most Value" (Page 499): "…many of the commonly successful strategies like buying stocks with the lowest price-to-earnings, price-to-cash flow or price-to-sales ratios significantly enhanced the returns of a small capitalization strategy. The value composites proved to be excellent measures of the health of small-cap stocks… The best-performing strategies also perform consistently… There is a red flag here, however. Even the best strategies suffered declines of 50 percent or more…"

From Chapter 24, "Sector Analysis" (Page 545): "…what works in the All Stocks universe also works quite well at the sector level. …what we should avoid investing in at the All Stocks universe level should also be avoided at the sector level."

From Chapter 25, "Searching for the Ideal Growth Strategy" (Page 567): "One of the very best ways to use price momentum is to marry it to a value constraint [composited value factors]. …six-month price appreciation is a more effective final momentum filter than 12-month price appreciation."

From Chapter 26, "Searching for the Ideal Value Stock Investment Strategy" (Page 578):

> "While I have added the growth requirement that three- and six-month price appreciation be greater than average, …the return differences are very small between the [value] strategy with that price momentum and without it."
>
> From Chapter 27, "Uniting the Best from Growth and Value" (Page 581): "One of the consistent themes of my research is the efficacy of uniting value and growth factors. Doing so allows you to smooth out the jags of a pure momentum strategy by tempering it with the best of value."
>
> From Chapter 28, "Ranking the Strategies" (Pages 595-596): "Each of the ten best-performing strategies…includes relative strength criteria. Yet they are *always* tied to another factor, usually one requiring the stocks to be modestly priced in terms of how much you are paying for every dollar of sales, earnings, book value, or a combination of value factors. Most of the 10 worst-performing strategies buy stocks that investors have bid to unsustainable prices, giving them astronomical price-to-earnings, price-to-book, price-to-sales, or price-to cash flow ratios, or are last year's biggest losers."

In summary, *investors will likely find* What Works on Wall Street *useful as a broad survey of the long-term historical performance of a large number of U.S. stock portfolios formed based on single and composite/combined indicators, converging to a few value-momentum strategies that work best on a gross basis.*

The book presents detailed results via a large number of figures and tables. It cites a reasonably wide range of supporting research, but citations concentrate in the late 1980s and early 1990s.

Cautions regarding findings include:

- The author focuses on portfolios of U.S.-listed equities (for which long-term data is most robust). It does not address diversification across global markets or different asset classes.
- While the author takes steps to mitigate data snooping bias, there are so many characteristics/combinations tested on the same data sets in search of best portfolio strategies that discrimination among strategies/variations may derive materially from luck.
- As acknowledged by the author, return calculations are gross of trading frictions for initial portfolio formation and annual rebalancing. The discussion in Chapter 4 on how the reader should correct for trading frictions (reference "Trading Frictions Over the Long Run") seems unsatisfying, as follows:
    - There may be interactions between level of trading frictions and return anomalies, such that anomaly existence depends materially on excluding frictions. For example, small-capitalization stocks generally carry higher trading frictions than large-capitalization stocks.
    - Because different strategies may have different levels of portfolio turnover, including trading frictions may affect the performance ranking of the strategies. For example, momentum strategies generally involve higher portfolio turnover than value strategies.
    - For individuals forming their own portfolios, holding enough stocks to exploit

historical statistics reliably means relatively small positions with attendant high trading frictions.

See “Out-of-Sample Test of What Works on Wall Street (O’Shaughnessy’s Cornerstone Strategies)” for true out-of-sample tests of two mutual funds implementing the author’s previously advocated strategies. See O’Shaughnessy Mutual Funds for the performance of three mutual funds introduced in 2010.

Originally published at http://www.cxoadvisory.com/17768/fundamental-valuation/a-few-notes-on-what-works-on-wall-street/ on November 25, 2011.

Out-of-Sample Test of What Works on Wall Street (O'Shaughnessy's Cornerstone Strategies)

November 25, 2011

In the mid-1990s, James O'Shaughnessy identified "cornerstone value" and "cornerstone growth" as best-of-breed equity investment strategies. The former emphasizes dividends among large-capitalization stocks, and the latter momentum/earnings growth for a broader universe. Based on Standard and Poor's Compustat data, he found that the value (growth) strategy returned an average 15% (18%) per year over a backtesting period of 1952-1994, compared to 8.3% for the S&P 500 Index. He implemented these two strategies in late 1996 via mutual funds and publicized them in early editions of his book *What Works on Wall Street: A Guide to the Best-Performing Investment Strategies of All Time*. He subsequently sold the mutual funds (which apply slightly different portfolio formation rules from those specified in the original research) to Hennessy Funds in 2000, where they survive as the Hennessy Cornerstone Value Fund (HFCVX) and the Hennessy Cornerstone Growth Fund (HFCGX). Has 14 years of out-of-sample performance of these two mutual funds confirmed the motivating backtests? Using self-reported annual total returns for HFCVX, HFCGX and selected benchmark indexes during 1997 through 2010, *we find that:*

According to Hennessy Funds, they specify the holdings of HFCVX and HFCGX annually by "strictly adhering to the following time-tested, quantitative formula[s]" applied to the Compustat database, as follows:

> **HFCVX** managers screen for large capitalization value firms (excluding utility companies) based on: (1) market capitalization above the average of the database; (2) number of shares outstanding above the average of the database; (3) 12-month sales 50% greater than the average of the database; and, (4) cash flow above the average of the database. They then select the 50 stocks with the highest dividend yield.
>
> **HFCGX** managers pursue a strategy that "marries value with momentum" via screening based on: (1) market capitalization above $175 million; (2) price-to-sales ratio below 1.5; (3) annual earnings higher than the previous year; and, (4) positive returns over the past three and six months. They then select the 50 stocks with the highest 12-month past return. [Item (1) may have grown over the years.]

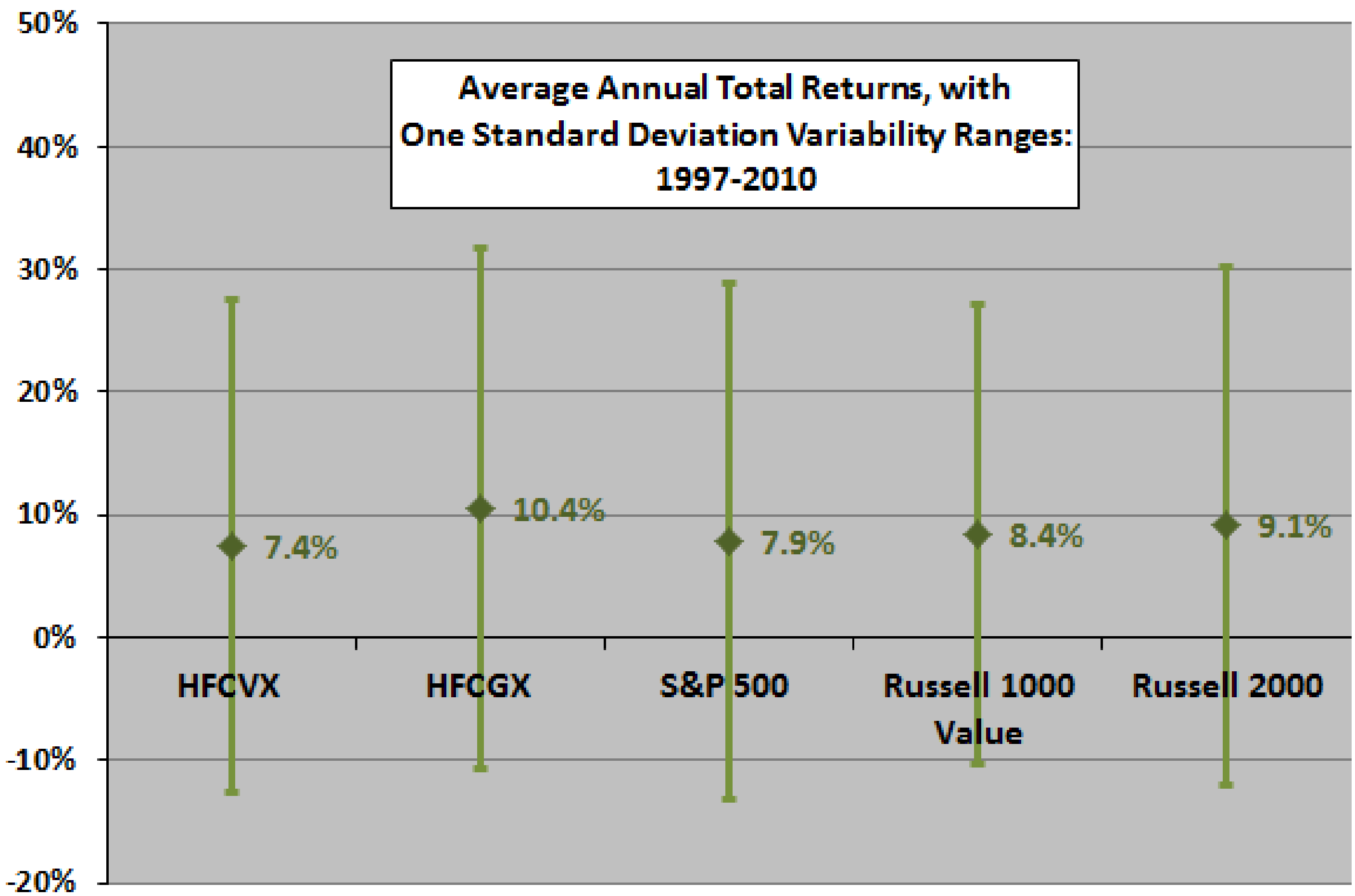
The following chart compares the average (arithmetic mean) annual returns of the funds and relevant benchmark indexes over the entire 1997-2010 sample period, with one standard deviation variability ranges.

HFCVX underperforms both its benchmark Russell 1000 Value Index and the S&P

500 Index. The fund underperforms the S&P 500 Index by about 0.5% per year, compared to the backtested average annual outperformance of about 7%. Also, its standard deviation of annual returns (20.1%) is higher than that for the benchmark Russell 1000 Value Index (18.7%). Backtested outperformance has not persisted over a 14-year out-of-sample implementation.

HFCGX outperforms both its benchmark Russell 2000 Index and the S&P 500 Index. The fund outperforms the S&P 500 Index by about 2.5% per year, compared to the backtested average annual outperformance of about 10%. Its standard deviation of annual returns (21.2%) is about the same as that for the benchmark Russell 2000 Index (21.1%). Backtested outperformance has persisted at a subdued level over a 14-year out-of-sample implementation.

For a different perspective, we look at cumulative returns.

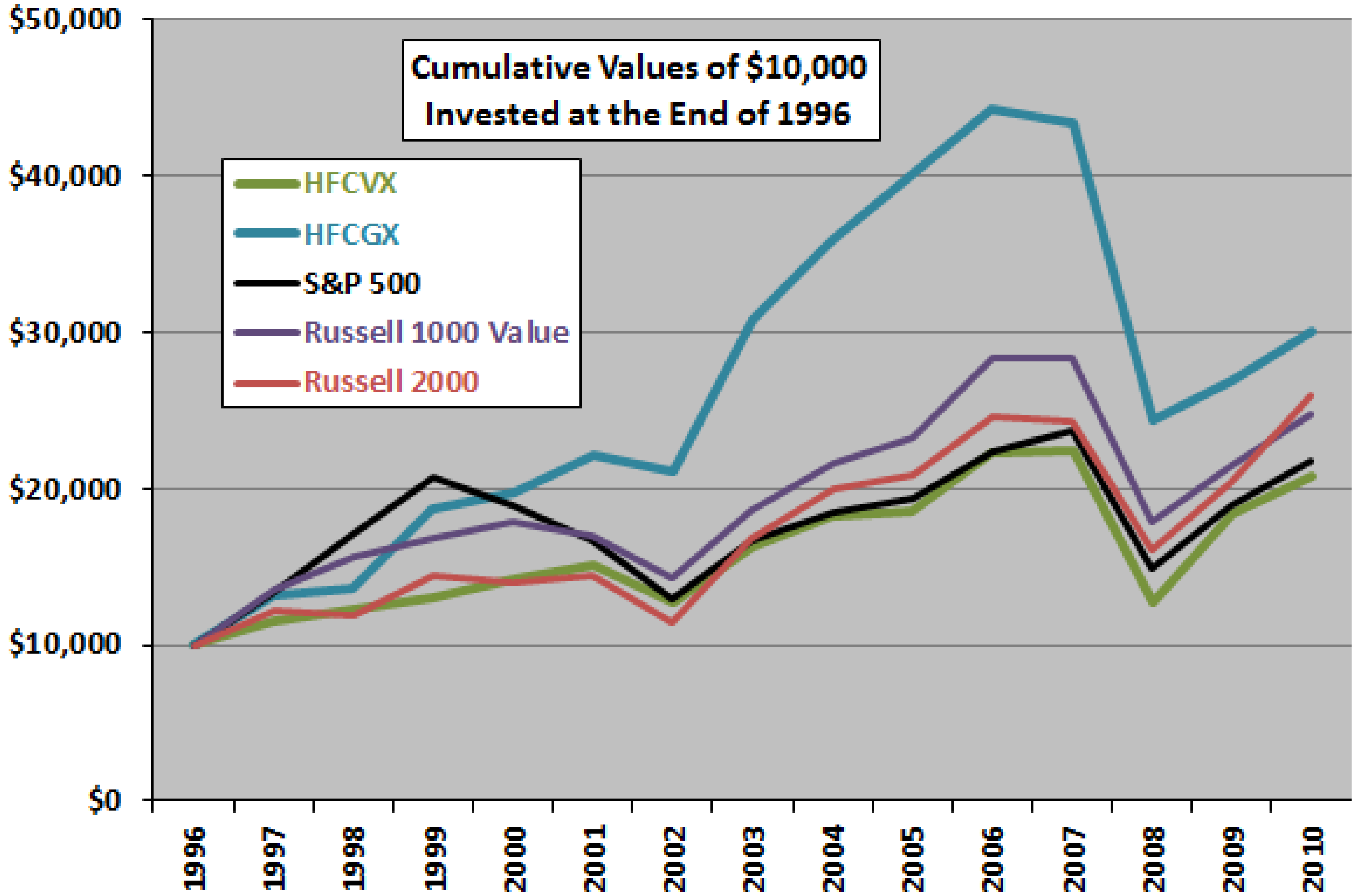


The next chart tracks the year-end values of $10,000 initial investments in each of HFCVX, HFCGX and benchmark indexes at the end of 1996 through the end of 2010. Results confirm that HFCVX (HFCGX) has consistently underperformed (outperformed) its benchmark index.

Possible reasons that the out-of-sample performances of these funds fall well short of their backtested performance are:

- The out-of-sample test is short and unlucky for the strategies.

- Backtests exclude trading frictions.
- The market changed. For example, the expansion of stock buybacks in lieu of dividends is largely absent from the backtest period and may disrupt the dividend-based strategy of HFCVX.
- The market adapted since publication of the cornerstone strategies, with more and more investors competing for the abnormal returns from similar strategies.
- Data snooping bias added material helpings of luck to the backtested performance.
- Wildness (non-normality) of stock return distributions makes average past return unreliable as a measure of expected return.
- Deviations by the fund managers from the original backtest specifications suppressed strategy performance.



In summary, *as found for the "cornerstone" strategies, what worked on Wall Street in past decades may or may not work in future decades. Changing/adaptive investment environments, implementation compromises and frictions, bias derived from mining noisy data and non-normality of stock return distributions complicate strategy development.*

Originally published at http://www.cxoadvisory.com/2713/fundamental-valuation/out-of-sample-test-of-what-works-on-wall-street-oshaughnessys-cornerstone-strategies/ on November 25, 2011.

Active Beats Buy-and-Hold?

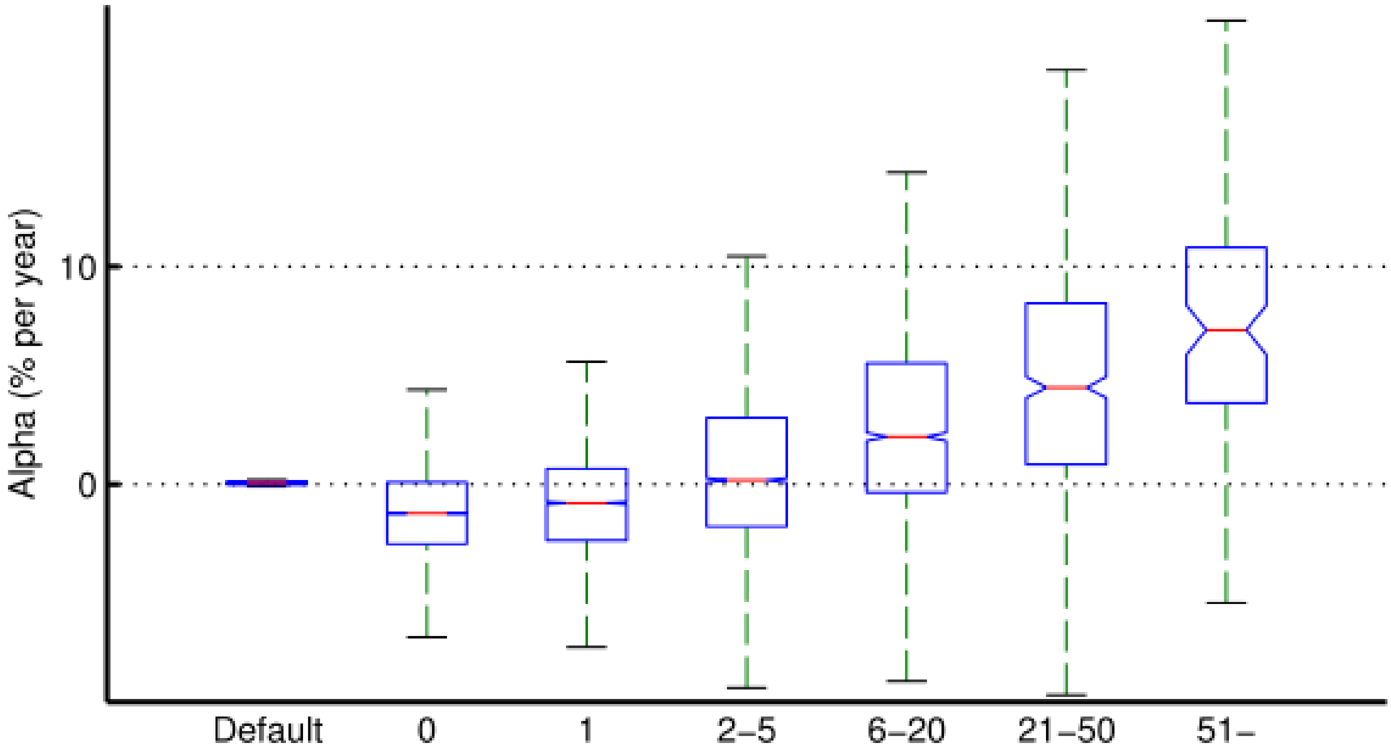
November 9, 2011

Do individuals who actively reallocate funds within their pension accounts outperform passive counterparts? In their October 2011 paper entitled "Individual Investor Activity and Performance", Magnus Dahlquist, Jose Vicente Martinez and Paul Soderlind examine the activity and performance of individual participants in Sweden's Premium Pension System. This system allows individual participants to reallocate among available mutual funds on a daily basis with no switching fees/impediments. Information about the 1,230 funds offered during the sample period includes type (fixed income, balanced, life-cycle and equity), return and risk measured at several horizons, fee and major holdings. Most are equity funds, about half of which invest primarily in international equities. The government assigns individuals who make no choice to a default fund. Using daily net returns, fund trades and demographics for 70,755 individuals (from a random draw of individuals in the system over the entire period) and contemporaneous returns for several benchmarks during September 2000 through May 2010, *they find that:*

- About 69% of system participants (30% in the default fund and 39% in initial selections) make no change in allocation over the sample period.
- Individuals who make an initial selection but no subsequent changes earn an average annual return of 1.7%, compared to 2.5%-8.6% for those who change allocations. Both raw and risk-adjusted average returns increase systematically with level of switching activity. Based on regression, ten fund changes relate to a 1.1% performance improvement.
- The outperformance of active fund traders derives primarily from switching funds within an asset class (fund selection) and not across asset classes (market timing). Results suggest that active traders pursue momentum-like strategies, which would likely be costly to implement outside the pension system.
- Roughly 10% of system participants exhibit coordinated trading, attributable to common financial advisors. Coordinated investors accounted for about 80% of all fund changes in 2010, but only the most active among them outperform benchmarks.
- Results generally hold after controlling for age, gender and income.

The following chart, taken from the paper, shows the median (red line), 25th-75th percentile range (blue boxes) and 95% range (black lines) of alphas for non-coordinated pension system participants ranked by level of activity over the entire sample period. Alpha is relative to returns of the Swedish stock market, the Swedish bond market and the world stock market. The "Default" category consists of individuals that make no initial fund selection and do not trade. The category "0" consists individuals who make an initial fund choice but but no subsequent changes. Other categories consist of individuals who have reallocated one or more times.

Results indicate that more frequent reallocation means better performance.



In summary, *evidence from Sweden's Premium Pension System indicates that active mutual fund traders tend to outperform passive participants, when there are no trading frictions/ impediments (in other words, when passive investors help bear costs of momentum trading by active investors).*

Active mutual fund traders unprotected from switching frictions/impediments may perform differently.

Findings offer some indication that momentum trading of funds, with low trading frictions/ impediments, may beat the market.

Originally published at http://www.cxoadvisory.com/17502/individual-investing/active-beats-buy-and-hold/ on November 9, 2011.

Asset Class Momentum Strategy

November 8, 2011

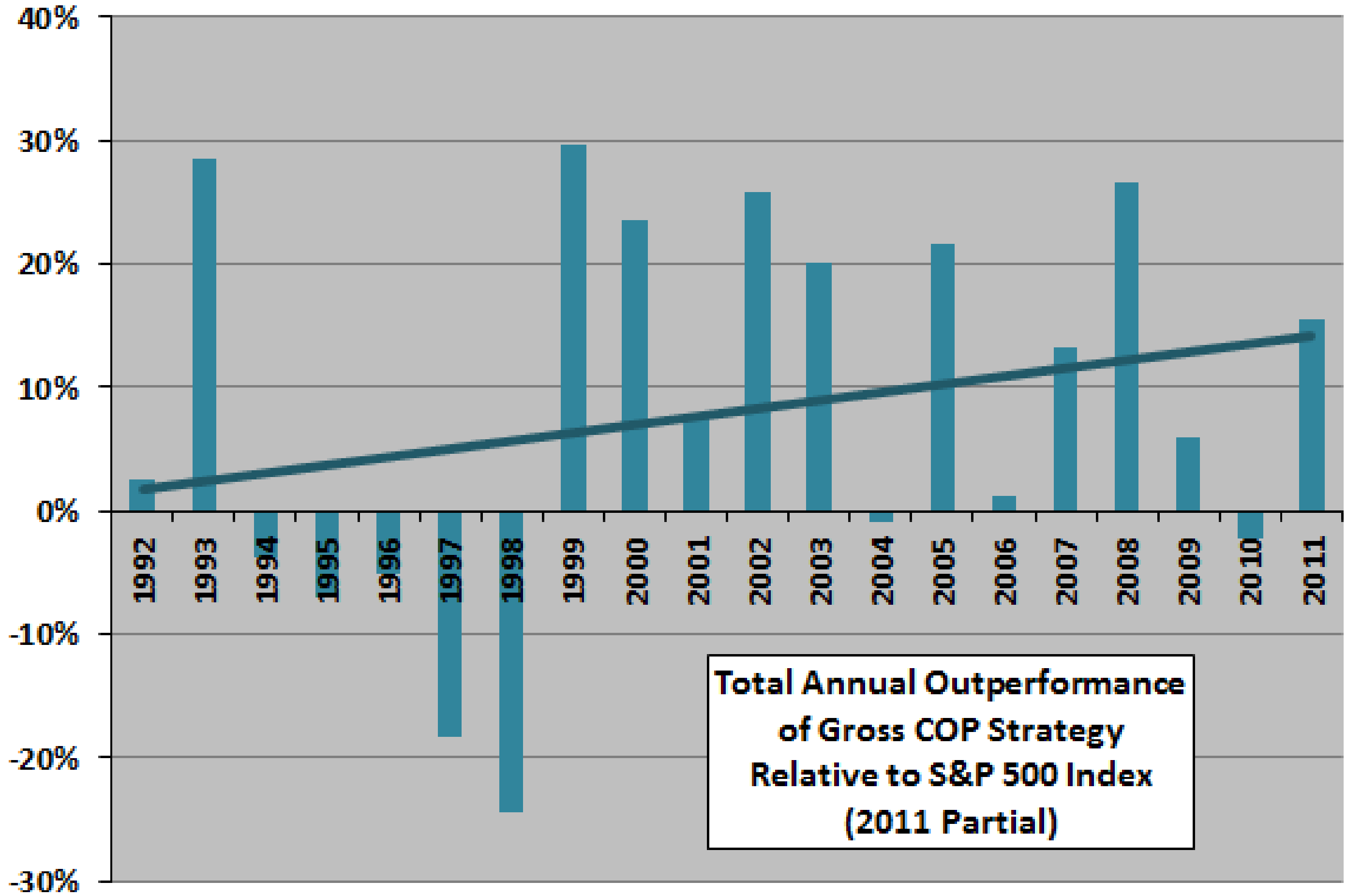
Do asset classes consistently exhibit momentum over the same time frame as stocks? In his January 2006 investing policy entitled "Class OutPerformance (COP) Strategy", Mal Williams describes a dynamic asset allocation strategy based on intermediate-term total return momentum of fund proxies (a complex calculation spanning the past 12 months, but not simply the 12-month return) for a wide range of asset classes. Implementation involves investing each month in the 10 to 15 best-performing funds out of a universe of 80 funds. In an October 2011 update of strategy tests, he selects the eight best-performing asset class proxies (heavily overweighting returns from the last three months) out of 51 possible as long as their performance is better than cash, in which case he allocates to the money market. He considers two implementation scenarios: (1) reallocate at the monthly open immediately after the fund ranking interval (for which there may be data availability issues); and, reallocate in the middle of the month after the ranking interval. Using monthly returns and semi-monthly prices for the 51 asset class proxy funds the period January 1991 through September 2011, along with contemporaneous money market yields, *he finds that:*

Because the COP strategy returns shown for 1991 are for the fourth quarter only, we start with 1992. During 1992 through (partial) 2011, the average annual gross return of the COP strategy implemented with a half-month delay after the ranking interval is 16.7%, compared to 8.7% for the total return of S&P 500 Index. Standard deviations of annual returns are 16.7% and 19.4%, respectively.

The following chart, constructed from the test results, depicts annual differences between the gross total return of the COP strategy implemented with a half-month delay after the ranking interval and the total return of the S&P 500 Index over the sample period, along with a linear best-fit trend line. Notable points are:

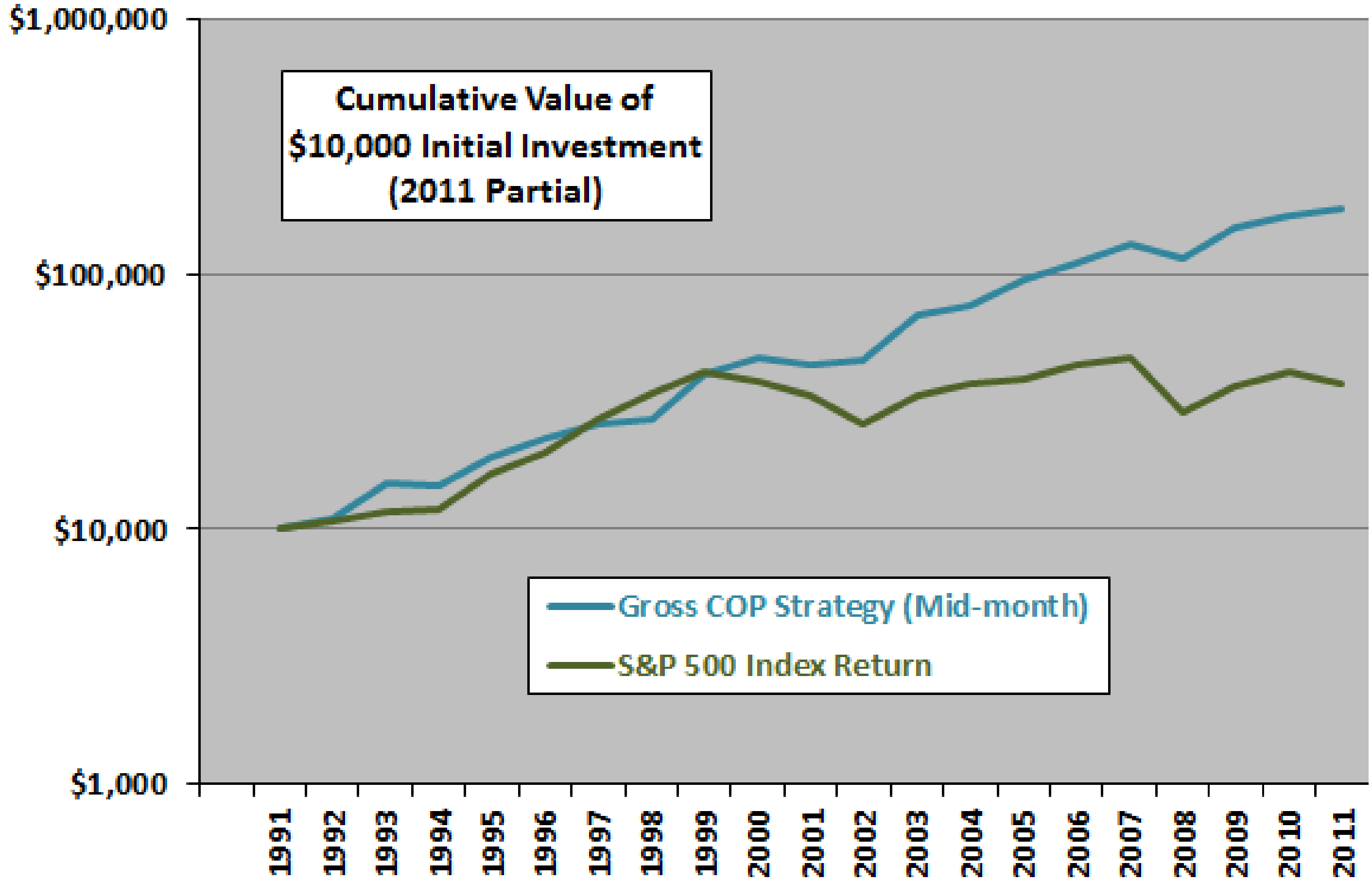
- COP outperforms the S&P 500 Index by an average 8.0% per year.
- COP beats the S&P 500 Index in 13 of 20 years (2011 partial).
- COP is relatively stronger in the latter part of the sample period (two bear markets) than the early part (including an extended bull market).

For another perspective, we look at cumulative results.

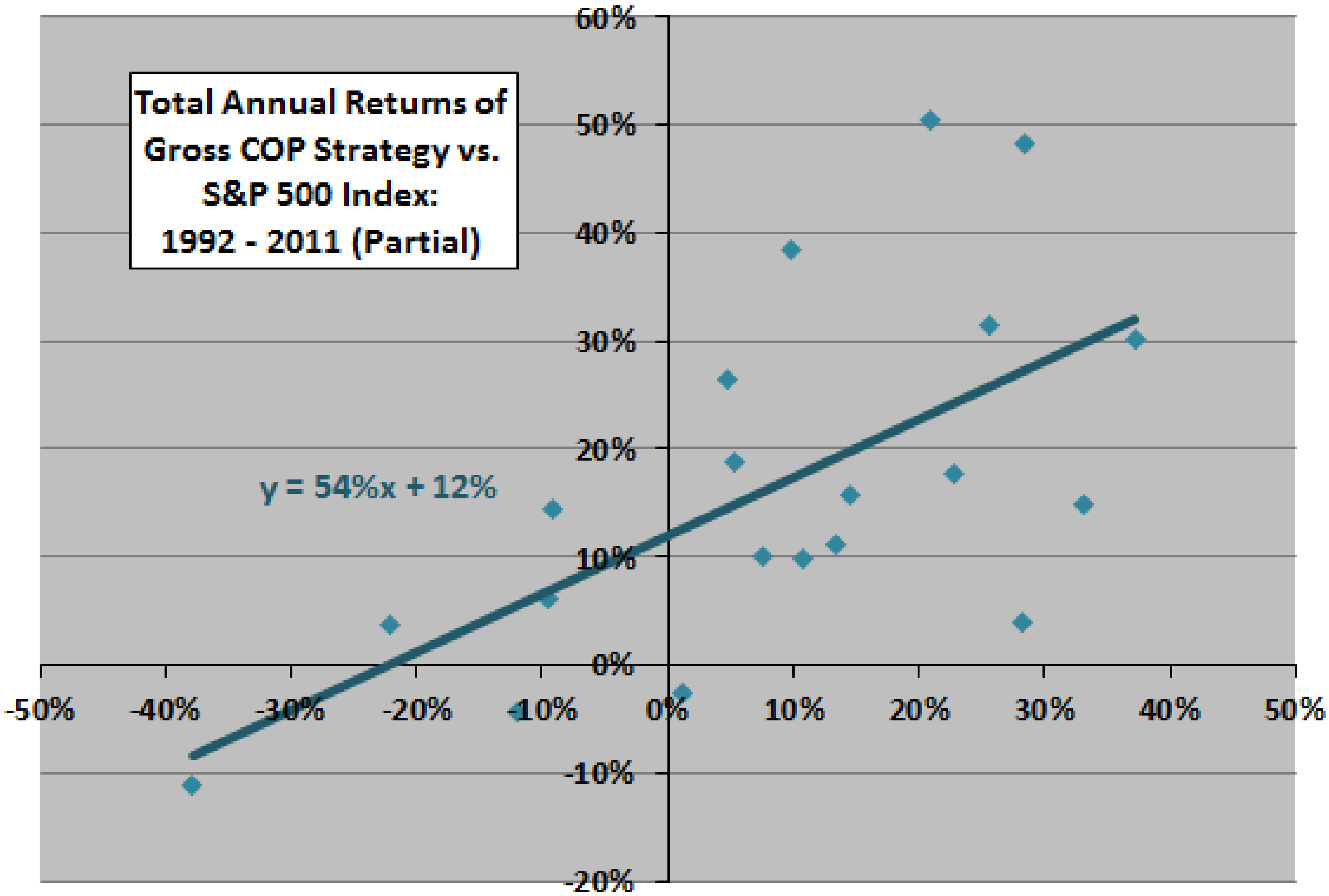


The next chart, also constructed from the test results, compares on a logarithmic scale the cumulative values of $10,000 initial investments at the beginning of 1992 through September 2011 in the gross COP strategy implemented with a half-month delay after the ranking interval and the S&P 500 Index (total return with dividends reinvested). Terminal values are $180,370 and $37,323, respectively. Results show that the COP strategy approximately tracks the S&P 500 Index during 1992-2000 and consistently outperforms thereafter.

For a third perspective, we look at a scatter plot.



The final chart, also constructed from the test results, relates the annual gross return for the COP strategy implemented with a half-month delay after the ranking interval to same-year total return for S&P 500 Index over the sample period. The COP strategy has a beta relative to the S&P 500 Index of 0.54 and an annual alpha of 12%.



In summary, *evidence indicates that asset classes exhibit intermediate-term momentum that may support a rotation strategy pursuing hot asset classes.*

Cautions regarding findings include:

- Since the COP strategy encompasses many non-equity and global asset classes, some passive mix of asset classes may be a more appropriate benchmark than the S&P 500 Index.
- The sample period (about 20 years) is not long relative to the lagged return measurement interval (one year).
- Reported returns are gross, not net. Depending on turnover and account size, the approach of investing each month in the top eight or 15 asset class proxies may incur material trading frictions that reduce these returns.
- The complex calculation of fund momentum introduces discretionary parameters (weighting factors for returns over different parts of the past 12 months). Optimization of strategy performance relative to these parameters introduces data snooping bias, such that results likely incorporate luck and overstate reasonable expectations for future returns.
- The COP strategy likely generates many short-term capital gains.

Originally published at http://www.cxoadvisory.com/1132/momentum-investing/an-investors-asset-class-momentum-trading-strategy/ on November 8, 2011.

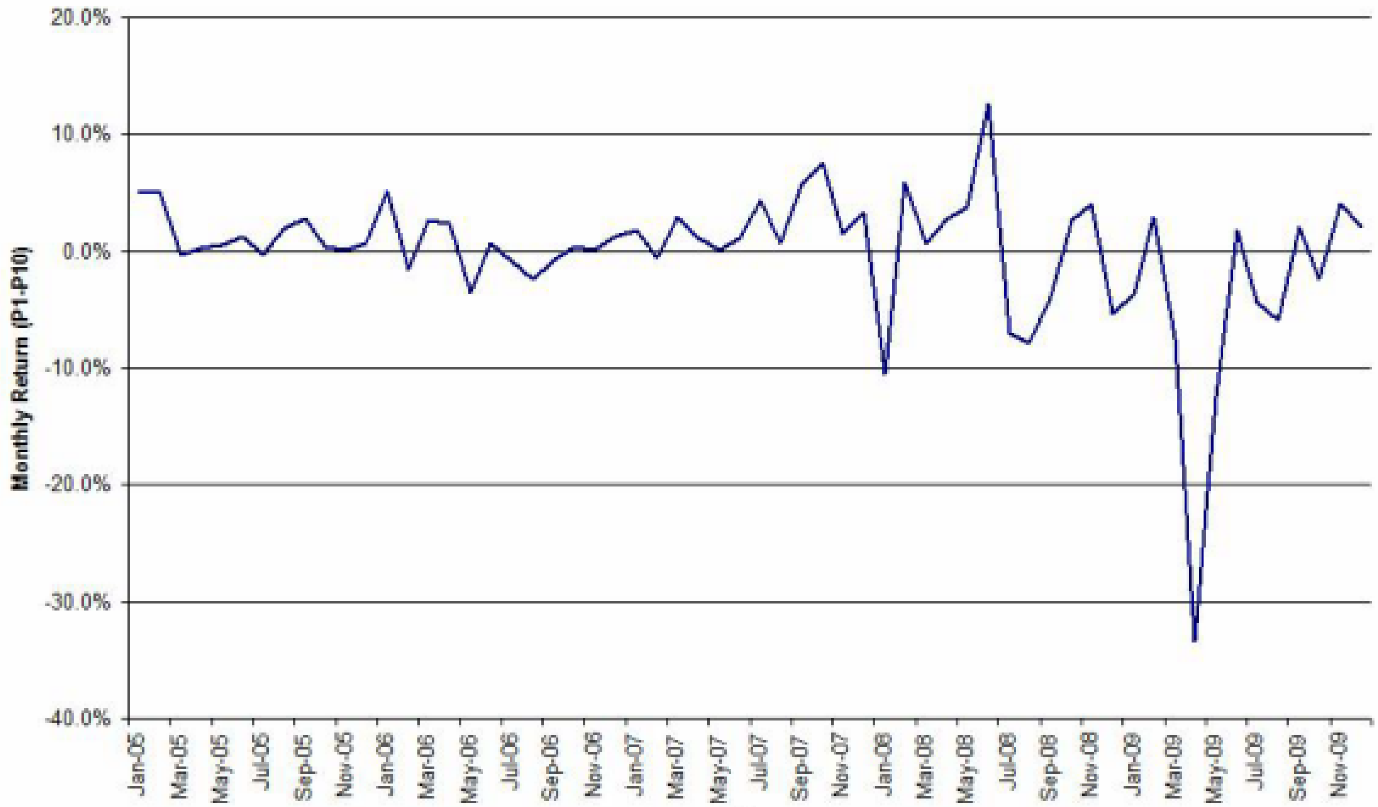
Momentum Not Working?

November 2, 2011

Is momentum on a losing streak? Or, has proliferation of momentum strategies extinguished the anomaly? In the October 2010 revision of his paper entitled "Are Momentum Strategies Still Profitable for U.S. Equity?", Scott Wilson examines the recent performance of a momentum hedge strategy that each month buys (sells) the tenth of stocks with the highest (lowest) lagged six-month returns. He employs (overlapping) six-month holding intervals and focuses on equal weighting of stocks at formation. Using monthly data for stocks traded on the NYSE, AMEX and NASDAQ, excluding the tenth with the smallest market capitalizations and those priced below $5, during 1965 through 2009, *he finds that:*

- Over the entire sample period, the selected hedge strategy generates an average gross monthly return of 1.14% over the six-month holding interval. Value weighting reduces this return to 0.98%.
- Segmenting the sample based on market capitalization confirms, as implied by the difference between equal and value weighting, that small stocks drive the momentum effect. Over the entire sample period, average gross monthly hedge strategy return progressively decreases across size quintiles from 1.32% for the smallest fifth stocks to 0.71% for the largest fifth of stocks.
- The selected hedge strategy is less profitable since 1998 and is actually unprofitable during 2005 through 2009 (see the chart below).

The following chart, taken from the paper, shows gross monthly returns for the selected momentum hedge strategy during 2005 through 2009. The strategy each month buys the tenth of stocks with the highest lagged six-month return (P1) and sells the tenth with lowest (P10), holding each such portfolio for six months, such that there are six active portfolios during each month. The return for each month is the average return for the six active portfolios. The overall average (median) gross monthly return for the strategy during this subperiod is -0.16% (0.70%).



In summary, *evidence from straightforward testing indicates that profitability of momentum investing in U.S. stocks has declined over time and disappeared in recent years.*

Cautions regarding findings include:

- Reported returns are gross, not net. Including reasonable trading frictions and shorting costs would reduce returns.
- A five-year subsample is quite small for inference regarding a strategy that involves six-month ranking and six-month holding intervals.
- Different ranking and holding intervals may enhance momentum strategy profitability compared to reported results (but optimization introduces data snooping bias). A market adaptation argument perhaps argues for shortening ranking and holding intervals.
- Adjacent ranking and holding intervals assume that an investor could slightly anticipate rankings to form portfolios at the same close.

See also “Disappearance of the Momentum Effect”, “Loss of Momentum?” and “Momentum Strategies Sputtering?”.

Originally published at http://www.cxoadvisory.com/17440/momentum-investing/momentum-not-working/ on November 2, 2011.

Harvesting Equity Market Premiums

October 31, 2011

Should investors strategically diversify across widely known equity market anomalies? In the October 2011 version of his paper entitled "Strategic Allocation to Premiums in the Equity Market", David Blitz investigates whether investors should treat anomaly portfolios (size, value, momentum and low-volatility) as diversifying asset classes and how they can implement such a strategy. To ensure implementation is practicable, he focuses on long-only, big-cap portfolios. To account for the trading frictions associated with anomaly portfolio maintenance and for time variation of anomaly premiums, he assumes future (expected) market and anomaly premiums lower than historical values, as follows: 3% equity market premium; 0% expected incremental size and low-volatility premiums; and, 1% expected incremental value and momentum premiums. He assumes future volatilities, correlations and market betas as observed in historical data and constrains weights of all anomaly portfolios to a maximum 40%. He considers both equal-weighted and value-weighted individual anomaly portfolios, and both mean-variance optimized and equal-weighted combinations of market and anomaly portfolios. Using portfolios constructed by Kenneth French to quantify equity market/anomaly premiums during July 1963 through December 2009 (consisting of approximately 800 of largest, most liquid U.S. stocks), *he finds that:*

- Both equal-weighted and value-weighted individual anomaly portfolios exhibit attractive Sharpe ratios and market alphas, with equal-weighted stronger. However, evidence for the size premium is relatively weak.
- Correlations among the market alphas of the anomaly premiums range from -0.45 and 0.64, indicating distinct effects and potential diversification benefits.
- The mean-variance optimized combination of portfolios makes large allocations to the value, momentum and low-volatility portfolios and none to the market and size portfolios, producing an expected Sharpe ratio 25%-30% higher than that of the market portfolio. The expected Sharpe ratio of the simple equal-weighted combination of market and anomaly portfolios (see the table below) slightly outperforms the mean-variance optimization.
- Efficient risk management indicates allocating to equity premium anomalies by strategic choice rather than tactical adjustment.

The following table, extracted from the paper, compares conservatively estimated future (expected) net and historical performances of the market (benchmark) portfolio, an equal-weighted combination of the market and anomaly portfolios and a mean-variance optimized combination of these five portfolios. Expected return calculations use the assumptions stated above. Historical returns ignore portfolio maintenance (trading) frictions and management fees.

Results show that diversification across equity anomaly portfolios reduces volatility, enhances return in excess of the Treasury bill yield and therefore increases Sharpe ratio compared to the market portfolio.

The paper includes similar, somewhat less attractive, results for value-weighted individual anomaly portfolios.

	benchmark portfolio	equally-weighted premium portfolios simple 1/N portfolio	optimized portfolio
portfolio weights			
market portfolio	100.0%	25.0%	-
small stocks	-	-	-
value stocks	-	25.0%	23.1%
momentum stocks	-	25.0%	40.0%
low-volatility stocks	-	25.0%	36.9%
return characteristics			
volatility	15.6%	15.3%	15.4%
expected excess return	3.0%	3.5%	3.7%
expected Sharpe ratio	0.19	0.23	0.24
historical excess return	3.9%	6.9%	7.8%
historical Sharpe ratio	0.25	0.45	0.51

In summary, *evidence indicates that investors may be able to improve risk/return performance in equities by strategically diversifying across reasonably liquid portfolios designed to exploit several conservatively derated stock market anomalies.*

Cautions regarding findings include:

- Even the conservatively adjusted estimates of net future anomaly premiums may be optimistic (especially for individuals with modest accounts). Implementation with exchange-traded or mutual funds may produce results different from those estimated with individual stock portfolios.
- As noted, results based on historical data are gross, not net. Including reasonable trading frictions for portfolio maintenance would materially reduce reported returns.

Originally published at http://www.cxoadvisory.com/17304/size-effect/harvesting-equity-market-premiums/ on October 31, 2011.

Statistically Recasting the Big Three Anomalies

October 28, 2011

Do the size effect, value premium and momentum effect derive from common firm/stock characteristics other than size, book-to-market ratio and past return? In the October 2011 version of their paper entitled "Which Firms Are Responsible for Characteristic Anomalies? A Statistical Leverage Analysis", Kevin Aretz and Marc Aretz statistically isolate and analyze the small minority of firms that drive these three anomalies. Specifically, they exclude firms from the sample experimentally to identify those stocks that contribute the most to each anomaly (exhibit the strongest statistical leverage) and then examine in several ways the characteristics and stock price behaviors of those firms. They define size based on market capitalization, value based on book-to-market ratio and momentum based on three-month past return (which exhibits stronger momentum than 12-month past return during the sample period). They form test portfolios annually on June 30 based on current size and momentum and six-month lagged book-to-market ratio and hold from July 1 to June 30 of the next year. Using monthly stock returns, stock trading data and accounting variables for the firms then included in the S&P 1500, along with contemporaneous benchmark data, during July 1974 through December 2007, *they find that:*

- Annualized anomaly magnitudes over the entire sample period are about 1.9% for the size effect, 4.0% for the value premium and 5.5% for the momentum effect.
- Excluding the 0.1% of stocks with the highest statistical leverage makes the size and the momentum effects disappear and cuts the value premium in half. Excluding the 1% of stocks with the highest statistical leverage reverses the signs of the anomalies. In other words, very small fractions of the sample drive all three anomalies.
- Stocks that have high statistical leverage for the value premium (size effect) tend to exhibit high idiosyncratic risk (high idiosyncratic risk and high default risk).
- No alternative variables explain a meaningful fraction of the momentum effect.
- There is hardly any support for the notion that trading costs explain the anomalies.

In summary, *evidence indicates that investors may be able to capture the traditional size effect and value premium more efficiently by focusing on stocks with high idiosyncratic volatility and high default risk.*

Cautions regarding findings include:

- Reported returns are gross, not net. Incorporating reasonable trading frictions would reduce these returns.
- The study appears not to account for any data snooping bias in testing explanatory values of many variables within the same data set.

Originally published at http://www.cxoadvisory.com/17262/size-effect/statistically-recasting-the-big-three-anomalies/ on October 28, 2011.

Intrinsic Momentum Investing

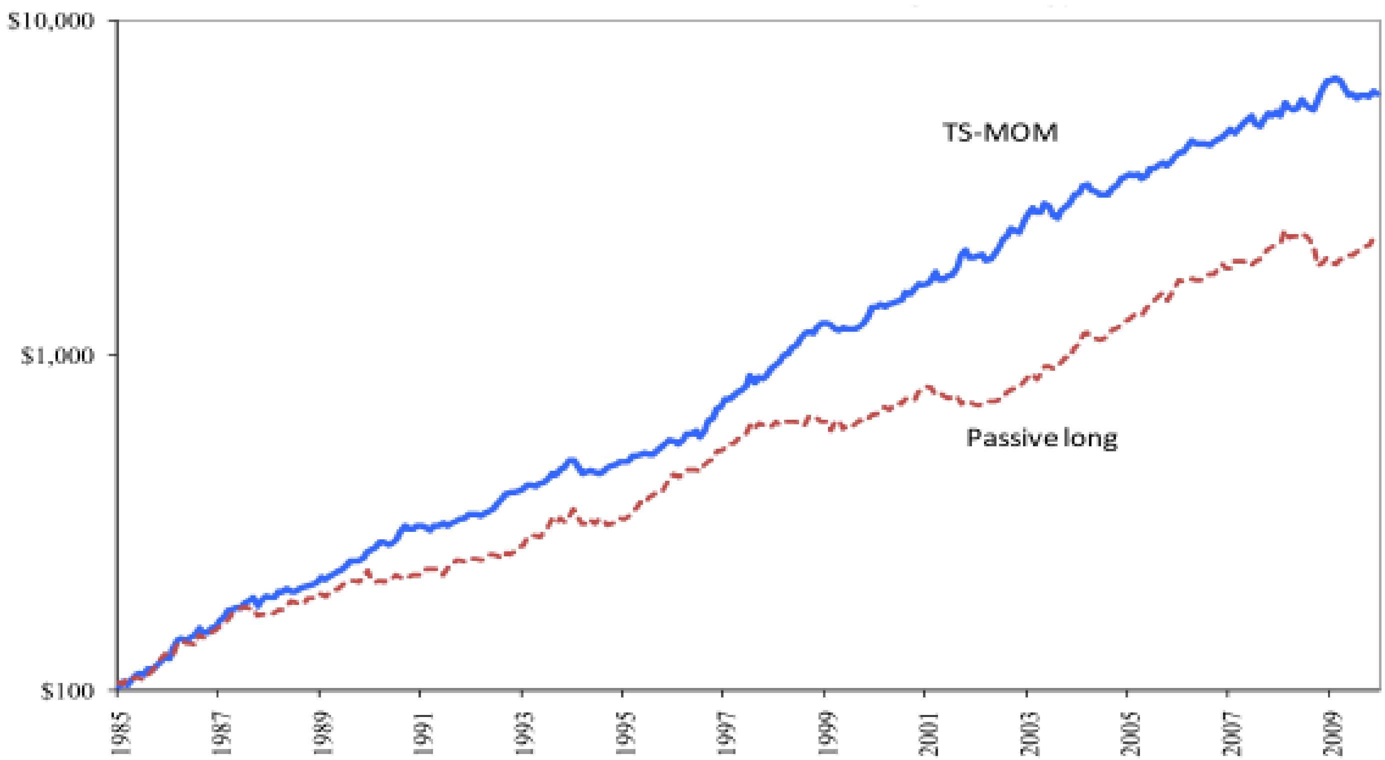
October 19, 2011

Most momentum investing strategies employ cross-sectional or relative strength by taking long (short) positions in assets exhibiting medium-term price strength (weakness). Is momentum also exploitable intrinsically, wherein an investor estimates momentum of an asset relative to its own medium-term history (time series)? In their August 2010 paper entitled "Time Series Momentum", flagged by a reader, Tobias Moskowitz, Yao Hua Ooi and Lasse Pedersen investigate time series momentum in liquid futures contracts (typically nearest or next nearest) spanning nine equity indexes, 12 currency pairs, 24 commodities and 13 government bonds. They focus on a (12-1) test strategy that each month takes a one-month long (short) position in each contract series with a higher (lower) return than Treasury bills over past 12 months. When combining different contract series into a portfolio, they weight each position to make an equal expected contribution to portfolio volatility (divide by lagged standard deviation of returns). Using daily prices for these 58 futures, Treasury bills and relevant benchmark indexes from 1985 through 2009, along with contemporaneous weekly Commitments of Traders (COT) reports as available from CFTC, *they find that:*

- Past excess returns of each futures contract series relate positively to its own future return for all series, with persistence up to 12 months that partially reverses over longer horizons. Findings are robust across subsamples, past return measurement intervals and holding intervals.
- Over the entire sample period, a diversified portfolio of 12-1 time series momentum strategies across all inverse volatility-weighted contract series delivers substantial and stable abnormal returns with little exposure to standard risk factors. Specifically:
  - The strategy generates a gross monthly alpha with respect to equities of about 1.26%, with insignificant dependence on market, size and book-to-market factors and positive dependence on a momentum factor.
  - Adjusted for a broader set of risk factors encompassing multiple asset classes, the strategy generates a gross monthly alpha of about 0.94%.
  - The strategy performs best during extreme markets and hence may serve as a hedge for extreme events.
- Time series momentum relates positively to traditional cross-sectional momentum, but still exhibits a gross monthly alpha of 0.66% relative to it.
- Both spot price momentum and the roll yield contribute to time series momentum of futures contracts, but only spot price changes drive long-term reversal.
- COT reports indicate that speculators profit from time series momentum at the expense of hedgers.

The following chart, taken from the paper, compares cumulative values of $100 initial investments at the beginning of 1985 in the diversified time series momentum (TS-

MOM) strategy and a diversified Passive Long position in all futures contract series (both weighted inversely on past standard deviation of returns) over the entire sample period. The TS-MOM strategy provides a comparatively steady stream of positive returns and terminal wealth about three times higher than the passive counterpart.



In summary, *evidence indicates that investors may be able to generate alpha by exploiting time series (intrinsic) momentum in futures contract series.*

Cautions regarding findings include:

- Reported returns are apparently gross, not net. Including trading frictions for monthly portfolio formation would reduce returns depending on position sizes and specific broker fees. The number of positions in the diversified portfolio is large (58).
- Daily capital (margin) requirements for the strategy are dynamic and unpredictable. It is not clear howreported returns/alphas translate to return on necessary capital reserves.
- Since strategy performance depends partly on roll yield, time series momentum may not work as well for underlying (spot) indexes as for futures contract series.

Originally published at http://www.cxoadvisory.com/17054/momentum-investing/intrinsic-momentum-investing/ on October 19, 2011.

When Momentum Does and Doesn't Work

October 14, 2011

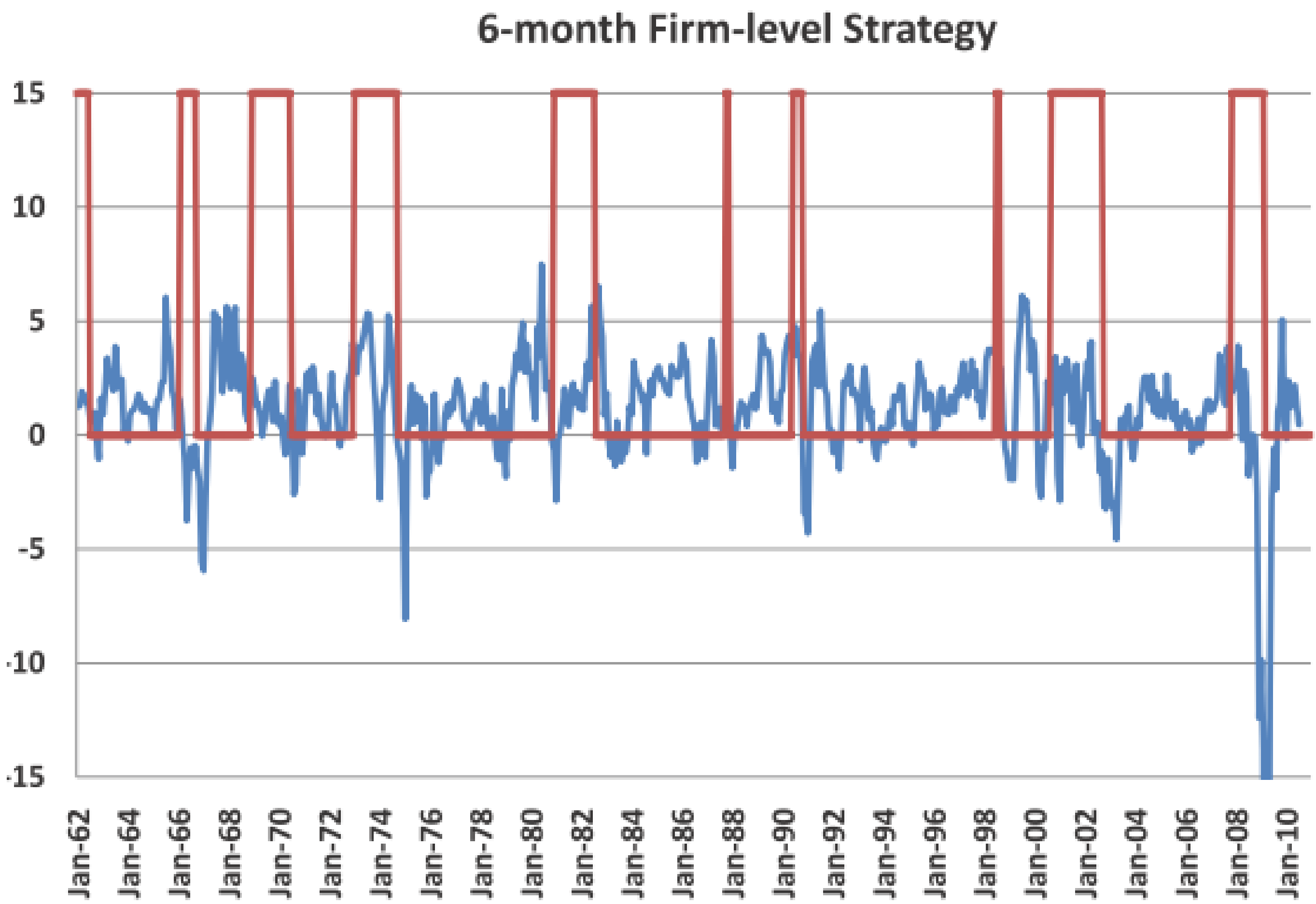
Does the effectiveness of momentum investing vary with market state? In the October 2011 version of their paper entitled "Market Cycles and the Performance of Relative-Strength Strategies", Chris Stivers and Licheng Sun investigate how market cycles (bull versus bear) affect the profitability of medium-term and long-term relative strength investing strategies. They consider both firm-level and industry-level value-weighted relative strength strategies with equal ranking and holding intervals of 6, 12, 18, 24 and 36 months (ten total strategies), with an intervening skip-month. For the firm level, strategies are long (short) the top (bottom) tenth of ranking interval winners (losers). For the industry level, strategies are long (short) the top (bottom) five ranking interval winners (losers). Bull (bear) market states are those following 15% cumulative advances (declines) from previous troughs (peaks). Using monthly return data for individual NYSE/AMEX stocks and for 30 value-weighted industries during 1962 through 2010, *they conclude that:*

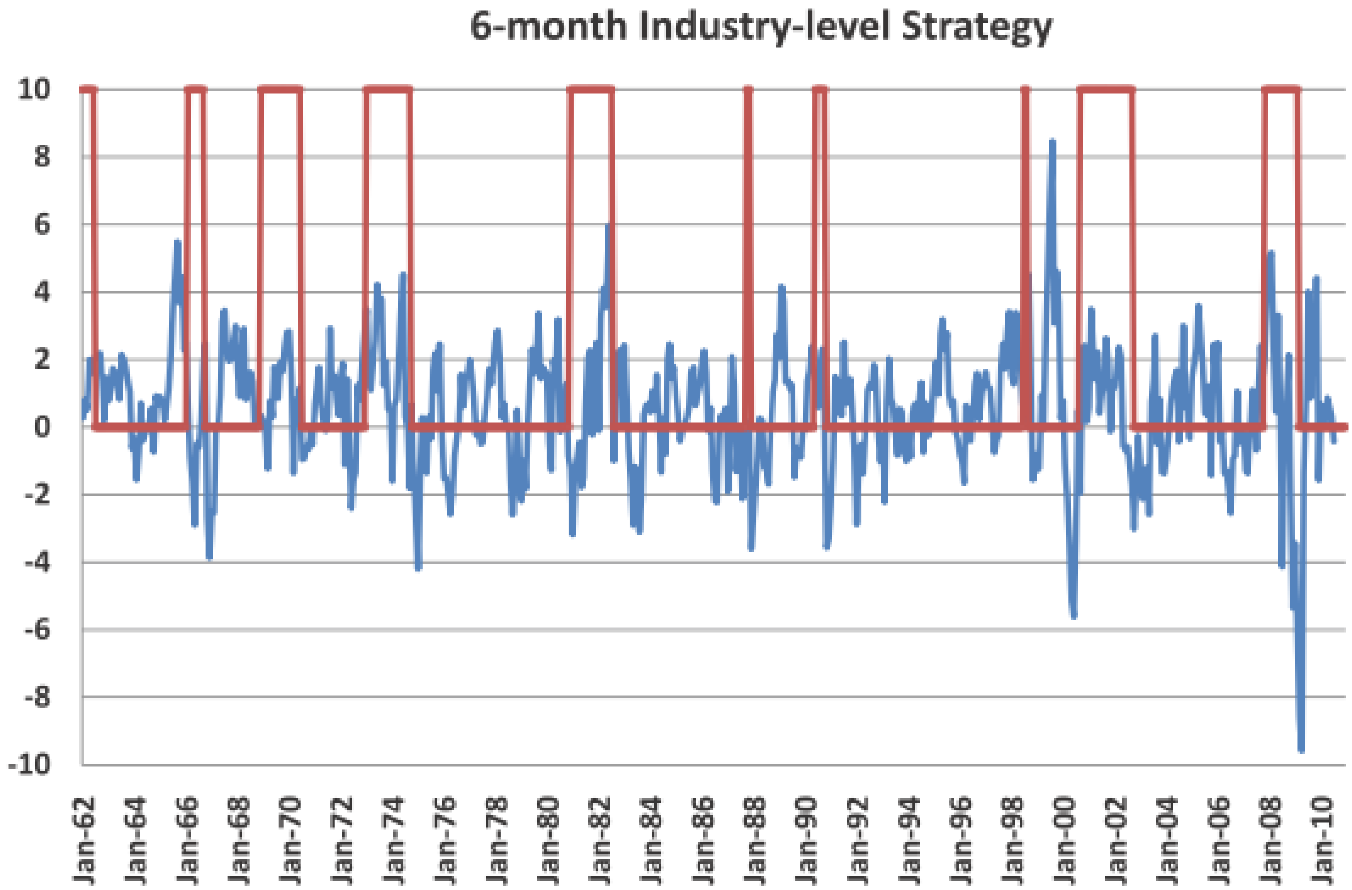
- Average gross profitability of relative strength strategies declines as ranking/holding interval increases.
  - At the firm level, average gross monthly profits decline from 1.12% for the 6-month interval to -0.80% for the 36-month interval.
  - At the industry level, average gross monthly profits decline from 0.55% for the 6-month interval to 0.07% for the 36-month interval.
- Based on the 15% advance/decline threshold, there are ten bull states and ten bear states during the sample period, with average (median) durations of 46.3 (36.5) months and 12.5 (12.0), respectively.
- Gross profitabilities of all ten strategies are materially higher when ranking and holding intervals are from the same market state, and extreme negative outcomes tend to occur around market state transitions.
  - For portfolios formed in April 2009 with exit from the 2007-2009 bear market, the cumulative gross return for the 6-month (12-month) relative strength strategy is -200% (-257%) at the firm level and -57% (-90%) at the industry level.
  - For portfolios formed in January 1975 with exit from the 1973-1974 bear market, the cumulative gross return for the 6-month (12-month) relative strength strategy is -48% (-17%) at the firm level and -25% (-16%) at the industry level.
  - For these shorter-interval strategies, average gross profits are materially lower during the second half of the sample period than the first half due to extreme negative returns around the 1991, 2002 and 2009 changes in market state.
  - Long bull markets indicate strong relative strength strategy performance.
- For all ten relative strength strategies, lagged cross-sectional dispersion of stock returns relates negatively to future performance. For example, when the lagged 3-month moving average of stock return dispersion is below (above) its 75th percentile, average future monthly gross returns are 0.42% (-1.46%) at the firm level and 0.34% (-0.58%) at the

industry level.

The following charts, taken from the paper, show as blue lines the performance of a relative strength (momentum) strategy with 6-month ranking and holding intervals applied at the firm (upper chart) and industry (lower chart) levels during 1962 through 2010. Returns are monthly percentages, calculated as the average over the holding interval. The red lines indicate bear markets (high value) and bull markets (low value).

Analysis indicates that the strategies perform poorly around times when the market is changing states.





In summary, *evidence indicates that momentum investing strategies are generally more profitable: (1) for shorter (6-month) ranking intervals; (2) when the stock market that is not shifting between bull and bear states; and, (3) when the dispersion of returns across individual stocks or industries is relatively low (high).*

It seems plausible that market adaptation to increasing use of momentum strategies may involve stronger and more frequent changes in market state.

Cautions regarding findings include:

- Return calculations are gross, not net. Trading frictions and costs of shorting would debit reported returns.
- As noted in "Momentum Overview from the Discoverers", using a skip-month for return ranking appears appropriate for individual stocks (firm level) but not industries.
- The authors select a 15% advance/decline threshold for defining a change in market state based on retrospective intuition. Some other market state indicator (such as 10-month simple moving average crossings) might work differently.

Originally published at http://www.cxoadvisory.com/1543/momentum-investing/when-momentum-does-and-doesnt-work/ on October 14, 2011.

The Decision Moose Asset Allocation Framework

October 7, 2011

A reader suggested a review of the Decision Moose asset allocation framework of William Dirlam. "Decision Moose is an automated framework for making intermediate-term investment decisions." Decision Moose focuses on asset class momentum, as augmented by monetary policy, exchange rate and interest rate indicators. Its signals tell followers when to switch from one index fund to another among nine encompassing a broad range of asset classes, including equity indexes for several regions of the globe. The trading system is a long-only approach that allocates 100% of funds to the index "having the highest probability of price appreciation." The site includes a history of switch recommendations since the end of August 1996, with gross performance. To evaluate Decision Moose, we assume that the 69 switches and associated trading returns are as described (out of sample, not backtested) and compare the returns to those for the dividend-adjusted S&P 500 Depository Receipts (SPY) over the same intervals. Using data for the 69 trades spanning 8/30/96 through 9/23/11 (15 years), *we find that:*

In calculating SPY total returns by Decision Moose trading interval, we assume trades occur at the close on Decision Moose signal dates, or at the close on the next trading day if signal dates are not trading days.

The following table summarizes gross Decision Moose trading results over the entire sample period (69 trades) and over the five years ending 9/23/11 (28 trades). Over the entire sample period (last five years), Decision Moose:

- Signals an average of about 4.4 (5.7) trading decisions per year.
- Generates a gross profit for 85% (79%) of trades.
- Outperforms buying and holding SPY by an average 4.3% (2.0%) return per trade.
- Outperforms buying and holding SPY during 58% (54%) of trading intervals.

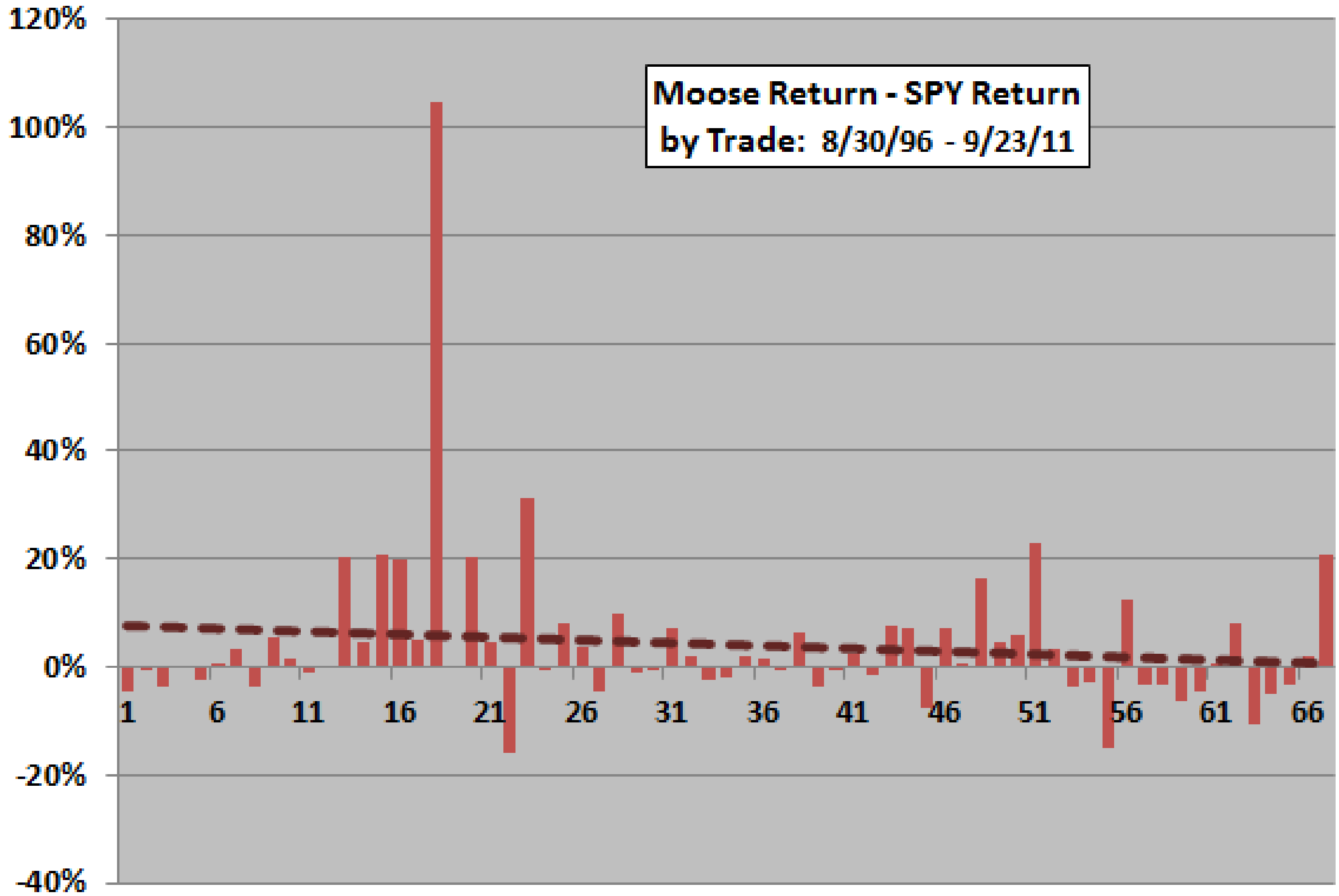
Including trading frictions would shave the outperformance of Decision Moose by a small percentage depending on specific broker fees, fund bid-ask spread and trader account size. For small accounts, this friction may have been important over the past five years.

Is the gross outperformance of Decision Moose relative to SPY persistent over time?

Decision Moose Perfomance	Trades	Average Trade Duration	Average (Moose Return - SPY Return)	Moose Return > 0	Moose Beats SPY
8/30/96 - 9/23/11	67	82	4.3%	85%	58%
8/18/06 - 9/23/11	28	67	2.0%	79%	54%

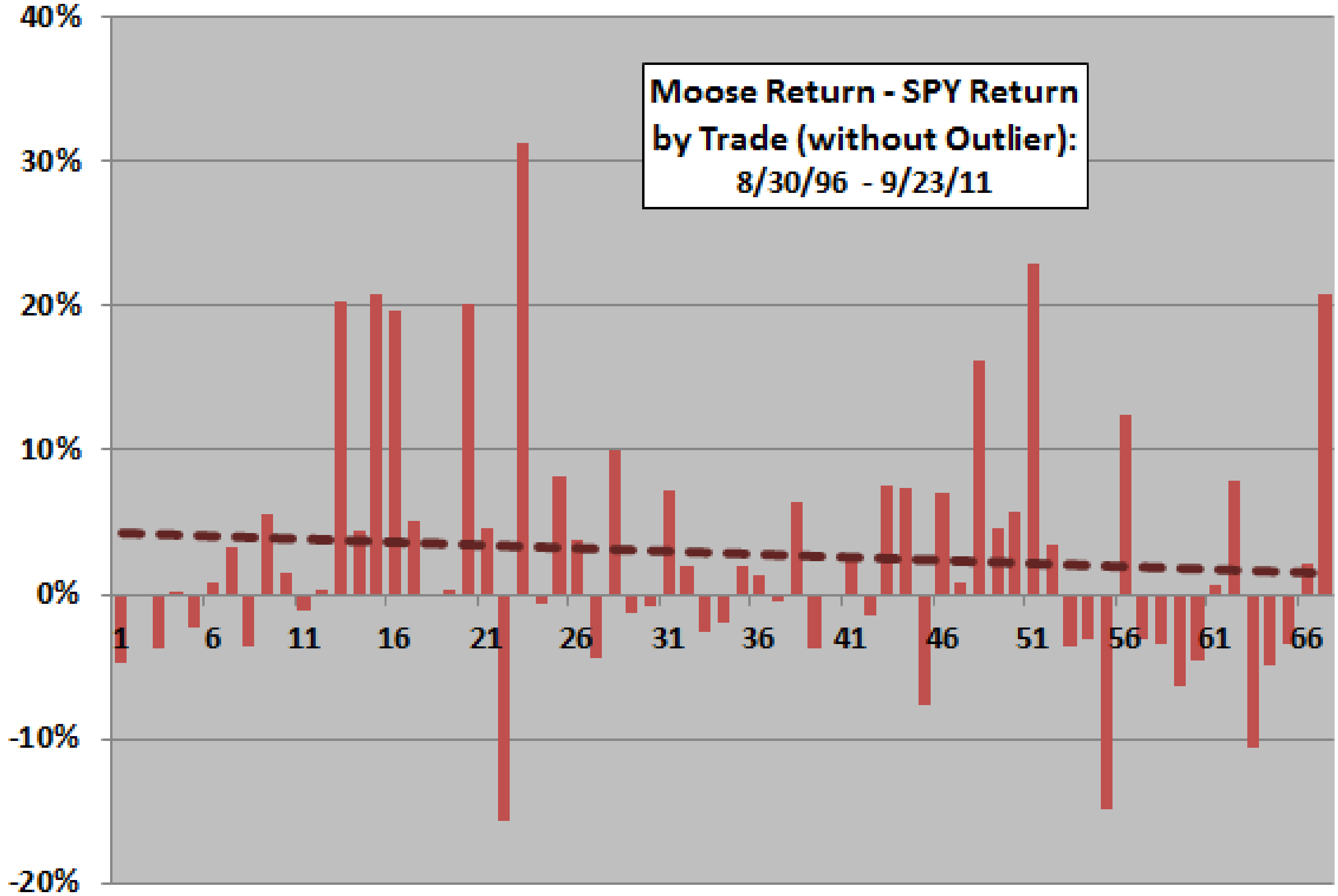
The following chart summarizes the differences between Decision Moose (Moose) gross returns and SPY returns by trade over the entire sample period, with a best-fit linear trend line. The trend line indicates that Decision Moose outperformance has dissipated over the sample period.

The sample size of 69 trades is not large. Might the Trade 18 outlier (gold during 11/24/01-6/1/02) be decisive in determining the trend?



The following chart summarizes the differences between Decision Moose gross returns and SPY returns by trade over the entire sample period, excluding the Trade 18 outlier. The best-fit linear trend line still indicates dissipation of Decision Moose outperformance over time, though not as severely as above.

The trend in outperformance by trade could be misleading because recent Decision Moose trading frequency is higher for the recent subperiod than for the overall sample period. What happens to the trend if we normalize trading results based on outperformance per calendar day?

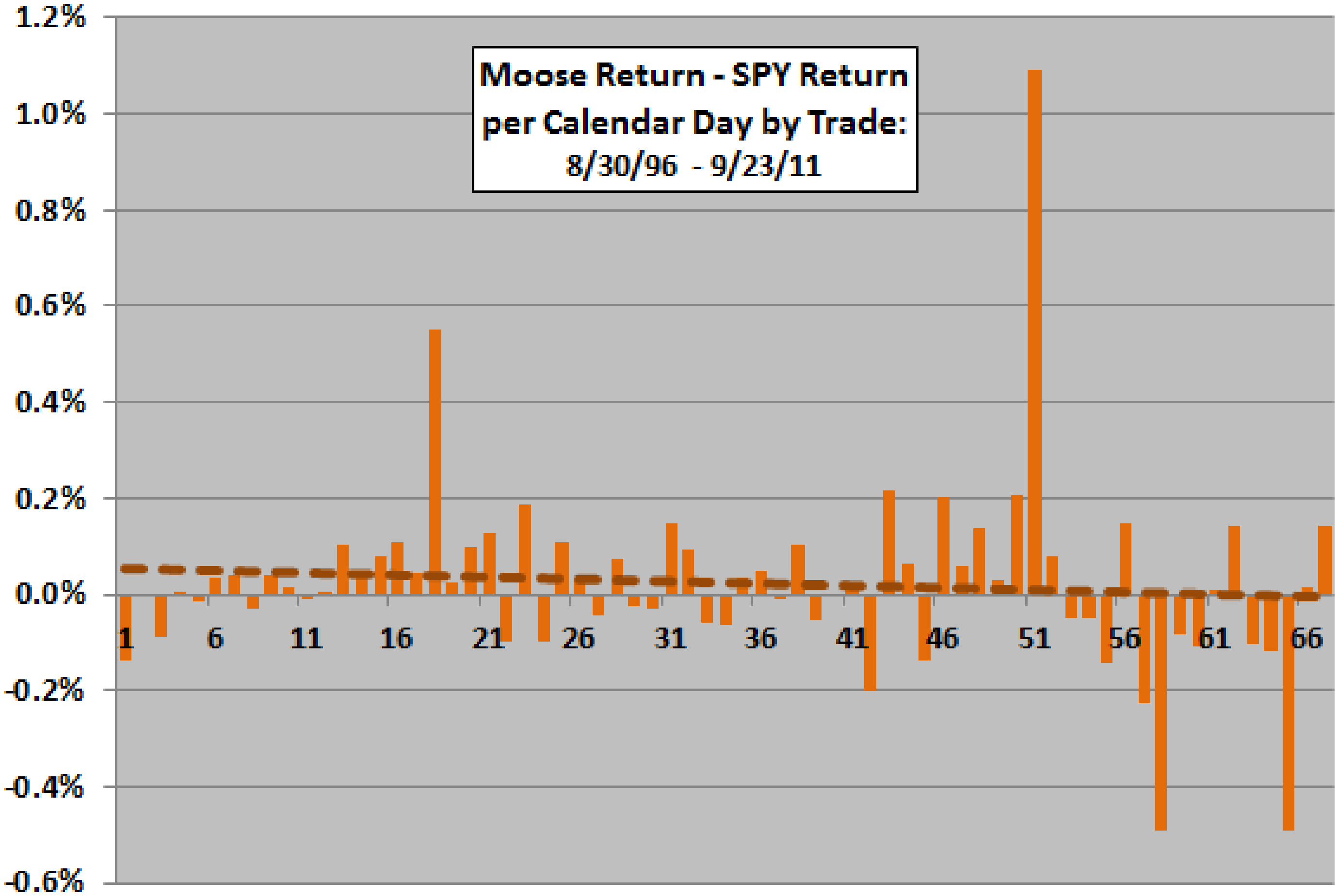


The following chart summarizes the differences between Decision Moose gross returns and SPY returns per calendar day by trade over the entire sample period. After this normalization, Trade 18 is no longer an obvious outlier. In fact, Trade 51 (avoiding much of the Fall 2008 crash) is the best normalized interval of outperformance.

The best-fit linear trend line indicates dissipation of Decision Moose normalized outperformance over time.

A plausible interpretation of these dissipation tests is that financial markets are adapting to increasing use of momentum-based tactical asset class allocation strategies. However, sample size is not large, and differences in outperformance over subperiods could be random.

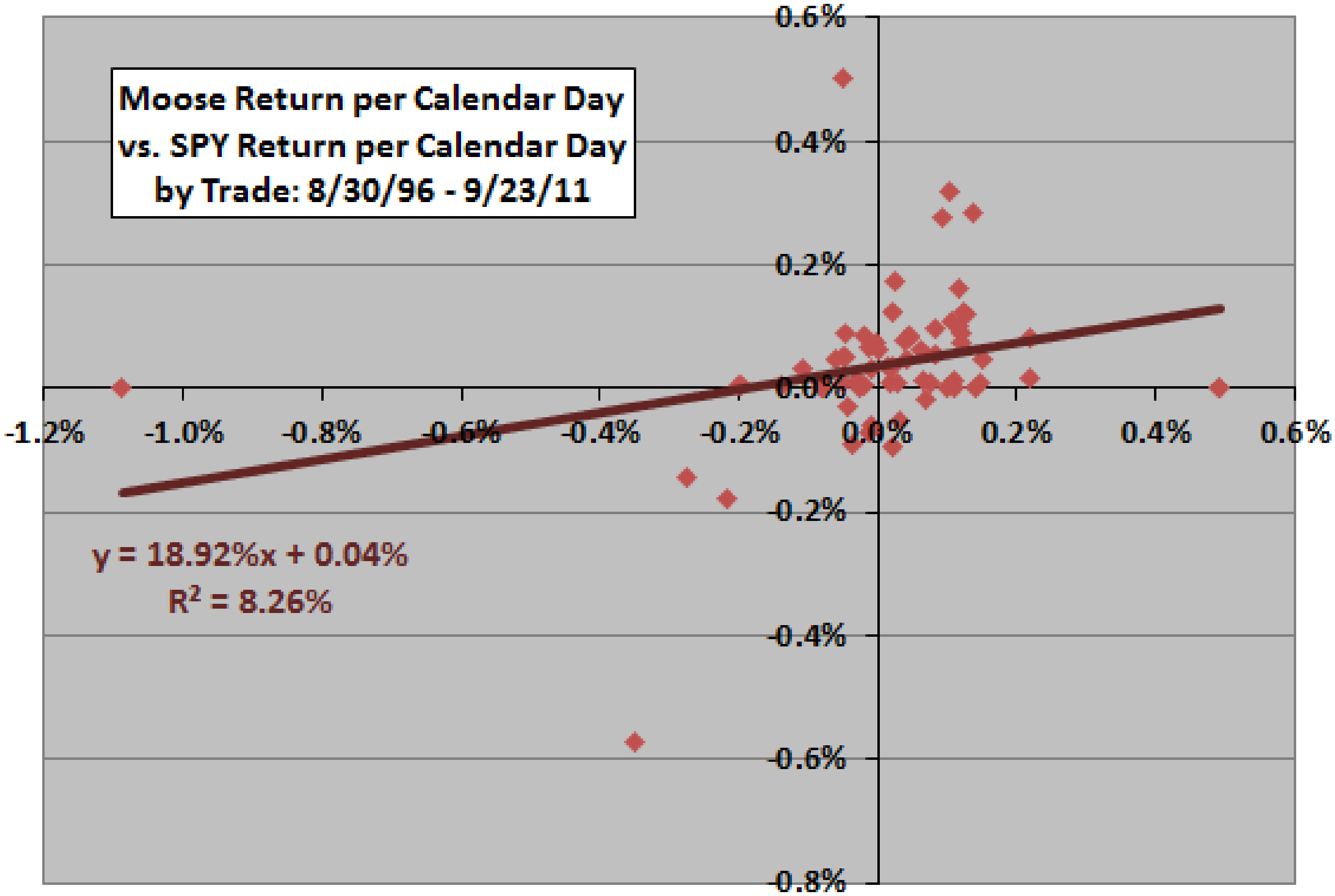
What does a regression show about the relationship between Decision Moose gross returns and SPY returns?



The following scatter plot presents a regression-based perspective on normalized gross Decision Moose performance over the entire sample period. Results indicate that:

- Decision Moose generates a gross daily alpha of about 0.04% relative to buying and holding SPY. (However, over the past five years, this alpha is only about 0.01%.)
- Decision Moose has a beta of about 0.19 relative to buying and holding SPY.
- SPY returns explain about 8% of Decision Moose returns (the R-squared statistic is about 0.08).

The latter two point indicate that Decision Moose returns are substantially independent of U.S. stock market performance.



In his FAQs, William Dirlam suggests that Decision Moose trading is best suited to reasonably large tax-deferred accounts to minimize the impacts of trading friction and taxes. He also offers guidance on the type of investor for whom Decision Moose is suitable.

In summary, *the Decision Moose asset allocation framework may offer investors a way to beat buying and holding the broad U.S. stock market by occasionally trading to the "hottest hand" (in economic context) from a set of nine asset class proxies, but its outperformance may be dissipating.*

Cautions regarding findings include:

- As noted, Decision Moose may not work well with small accounts for which taxes are not deferred.
- SPY may not be the most appropriate benchmark for Decision Moose, which employs nine distinct asset classes. (But an unreported test of Decision Moose versus a traditional 60% SPY-40% bond fund portfolio, frictionlessly rebalanced each time Decision Moose trades, yields results similar to those above.)

Originally published at http://www.cxoadvisory.com/2663/economic-indicators/the-decision-moose-asset-allocation-framework/ on October 7, 2011.

Disappearance of the Momentum Effect

September 30, 2011

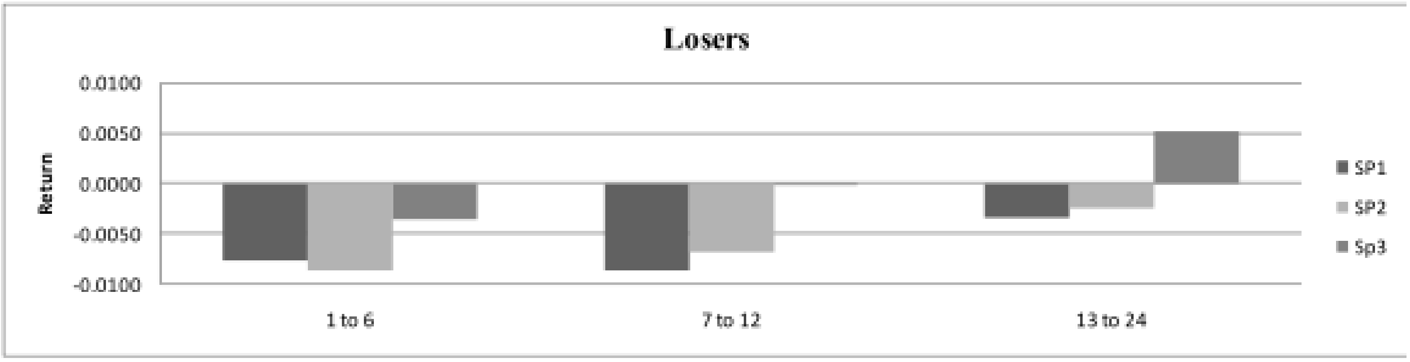
Has the stock market adapted to widespread investor efforts to exploit intermediate-term return momentum? In their paper entitled "Momentum Loses Its Momentum: The Implication on Market Efficiency", Debarati Bhattacharya, Raman Kumar and Gokhan Sonaer evaluate the robustness of momentum returns in the U.S. stock market over time via consideration of three subperiods: 1965-1989 (SP1), 1990-1998 (SP2), and 1999-2010 (SP3). They focus on SP3 to measure post-discovery persistence of the momentum effect. They form overlapping portfolios monthly by ranking stocks into deciles (tenths) based on six-month cumulative past returns and holding for six months or 12 months (and 24 months for one test). Using monthly returns and firm characteristics for a broad sample of U.S. stocks over the period 1965 through 2010, *they find that:*

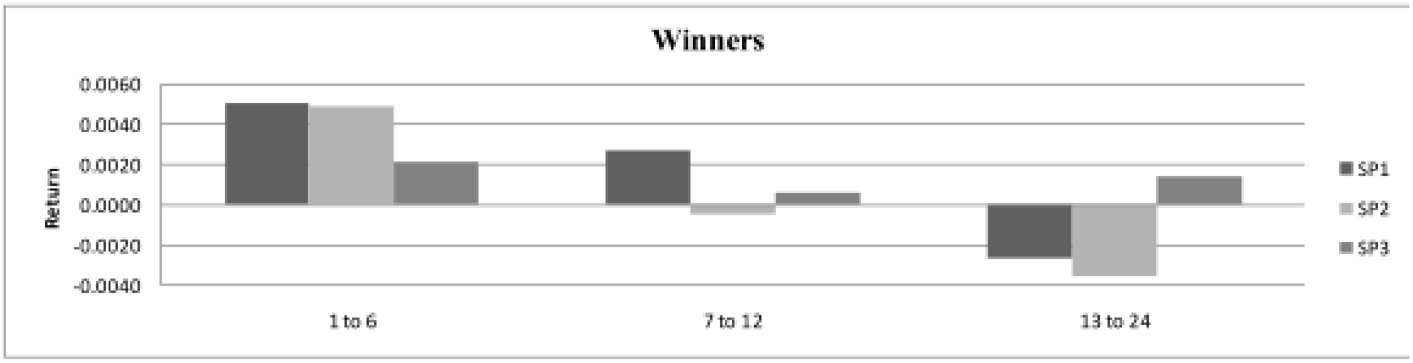
- A hedge portfolio that is long (short) the tenth of stocks with the highest (lowest) past six-month returns, reformed monthly, generates average monthly gross returns of 1.10% (1.37%) over a six-month holding interval during SP1 (SP2). However, during SP3, average monthly gross return declines to a statistically insignificant 0.72%. Results for a 12-month holding interval are somewhat lower for all three subperiods.
- The monthly three-factor (market, size, book-to-market) gross alpha for this strategy is 1.27% (1.35%) over a six-month holding interval during SP1 (SP2). However, during SP3, average monthly gross alpha declines to a statistically insignificant 0.57% (see the chart below). Results for a 12-month holding interval are somewhat lower for all three subperiods.
- During SP3, augmenting the Fama-French three-factor (market, size and book-to-market) model with a momentum factor fails to improve prediction of future stock returns.
- Results are robust to exclusion of "unusual" years during SP3 (and, in fact, SP2 arguably includes unusual years).

The following chart, taken from the paper, compares by study subperiod average gross three-factor alphas of stocks within the lowest (Losers) tenth and the highest (Winners) tenth of past six-month returns for extended holding intervals out to two years after portfolio formation. The chart shows that:

- Losers and Winners momentum during months 1-6 after portfolio formation is much lower for SP3 than for the two earlier subperiods.
- Losers and Winners exhibit no momentum during months 7-12 after portfolio formation for SP3.
- Average returns for both Losers and Winners during months 13-24 are quite different for SP3 compared to the first two subperiods.

Results suggest that dissipation of intermediate-term investor overreaction may explain the disappearance of momentum.





In summary, *evidence indicates that the gross profitability of intermediate-term return momentum for U.S. stocks dissipates considerably since the late 1990s, and that momentum may no longer qualify as a fourth return adjustment factor.*

Note that:

- Return and alpha calculations in the study are gross. Net values accounting for trading frictions would be materially lower.
- Data snooping bias related to subperiod selection may play a role in the flow and ebb of the momentum effect (as an adjunct or alternative to market adaptation).
- The statistical significance test used in the study assumes tame stock return distributions. To the extent that actual return distributions are wild, this test breaks down.

Also, a subscriber noted that the average monthly gross momentum alpha for the six-month holding period during SP3, which translates to an annualized alpha around 7%, still seems economically significant. Note that:

- The t-stat in the paper for SP3 momentum alpha is not high, indicating considerable variability in the data contributing to the average. In other words, a statistician would say that confidence in the SP3 momentum alpha being reliably different from zero is not high.
- The alpha is gross, and momentum portfolios reformed monthly tend to generate quite a bit of turnover and thereby burdensome trading frictions. It would be interesting to see whether relatively illiquid stocks contribute the lion’s share of the gross alpha, making trading frictions even more of a concern. In any case, a manager would not be able to extract 7% alpha before trading frictions, and the manager’s administrative fees would

further eat into any residual. See, for example, “Trading Friction as a Momentum Killer”.

- It would also be interesting to see whether the gross alpha is front loaded in SP3, indicating gradual (rather than stepwise) extinction. See the trend line in “The Decision Moose Asset Allocation Framework”.

See “Loss of Momentum?” for a similar study but some different angles.

Originally published at http://www.cxoadvisory.com/12064/momentum-investing/disappearance-of-the-momentum-effect/ on September 30, 2011.

Momentum Overview from the Discoverers

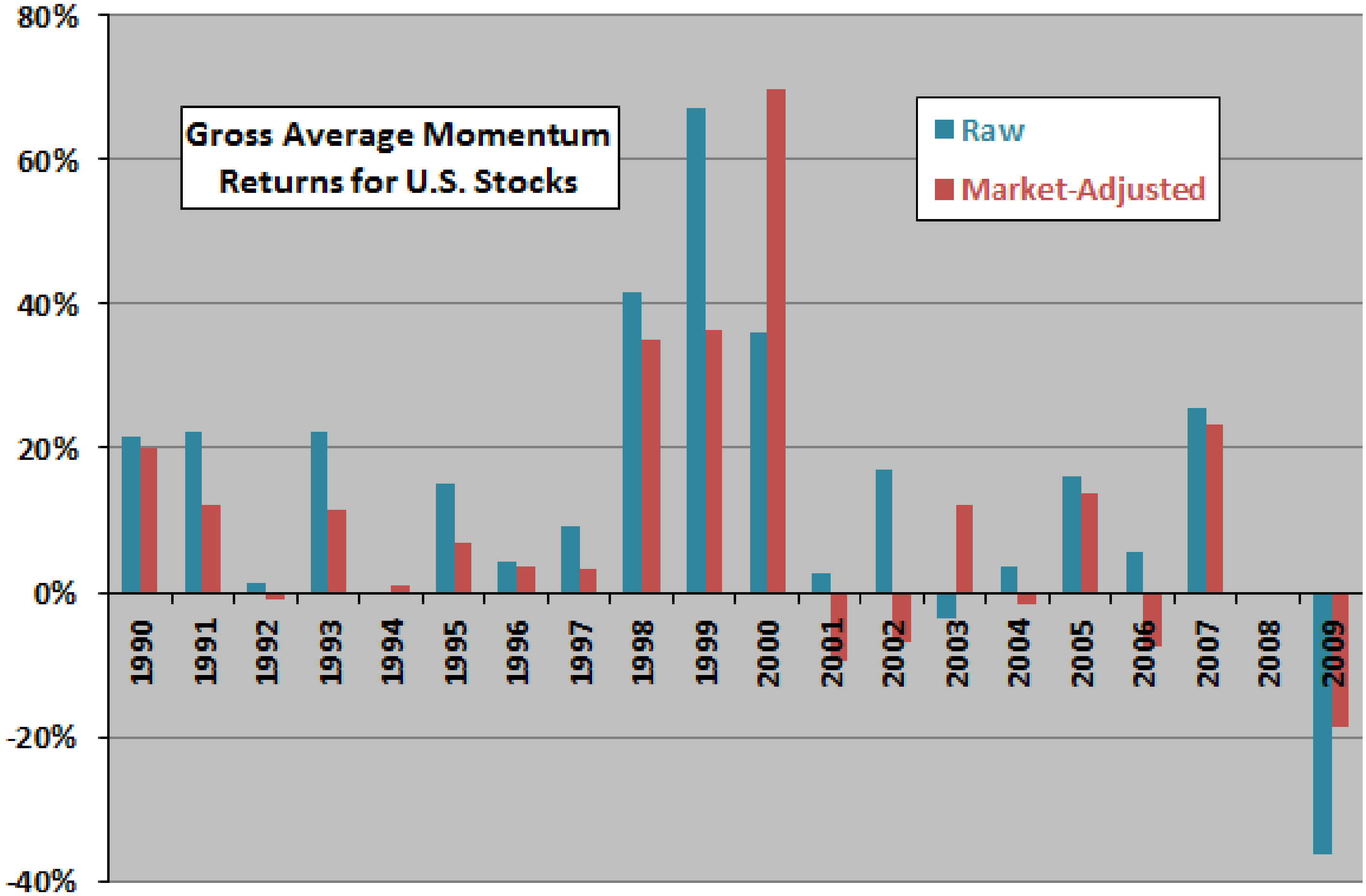
September 9, 2011

What is the state of momentum investing? In their January 2011 paper entitled "Momentum", Narasimhan Jegadeesh and Sheridan Titman summarize equity price momentum research and discuss explanations for the momentum anomaly. Specifically, they address equity momentum investing performance during 1990 through 2009, and the firm characteristics and market conditions that affect momentum returns. Based on a review of momentum research since 1990, *their key points are:*

- Considerable evidence indicates that stocks performing well (poorly) during the past three to 12 months tend to perform well (poorly) over the next three to 12 months. (See the chart below.)
    - A hedge portfolio that buys (shorts) the tenth of U.S. stocks with the highest (lowest) returns over the interval from seven months ago to one month ago and holds for six months is on average profitable before trading frictions in every five-year period starting in 1965 through 2003.
    - However, average gross profit for this strategy in the five-year period starting in 2004 is negative, driven mainly by extremely negative returns in 2009.
- Momentum strategies tend to be profitable at a gross level in most large stock markets, with Japan a notable exception. Some research suggests that markets in countries with more individualistic cultures exhibit stronger momentum.
- Momentum strategies tend to earn negative gross returns in January, but significantly positive gross returns in every other calendar month.
- Individual stocks (industries) appear to have negative (positive) serial correlation in portfolio returns, such that the associated momentum strategy should (should not) include a skip between the ranking interval and portfolio formation.
- There is generally some reversion of momentum profits for holding intervals longer than 12 months.
- Various studies find that momentum tends to be stronger:
    - For stocks with sparse analyst coverage, high book-to-market ratio, high dispersion in analyst earnings forecasts, high return volatility, high cash flow volatility, high revenue volatility, high turnover and low credit rating.
    - After recent periods of low market volatility and during times of strong investor sentiment.
- Similarly, stocks with strong earnings momentum tend to outperform stocks with low earnings momentum.
- Most evidence suggests that momentum derives from a delayed reaction (or overreaction) to firm specific information.

The following chart, constructed from data in the paper, summarizes average gross raw and market-adjusted returns by calendar year for a momentum strategy that each month buys (sells) winning (losing) stocks based on cumulative returns from seven months ago to two months ago (six-month past return with skip-month) and holds the resulting equally weighted, overlapping portfolios for six months.

The strategy generates a gross average profit in 16 out of the 20 years. The average annual gross profit is 13.5%, but with a severe loss of 36.5% in 2009. The poor performance of momentum investing in 2009 may be due to a confluence of unusual (1933-like) market conditions unfavorable to momentum.



In summary, *the preponderance of evidence indicates that stock price momentum is a fairly pervasive consequence of delayed investor reaction and is usually exploitable at a gross level, with various firm/stock and economic/market conditions enhancing or suppessing its strength.*

Cautions regarding findings include:

- Return calculations are gross, not net. Including reasonable trading frictions, which may be highest for the stocks contributing most to momentum portfolio performance, would reduce reported returns materially. (See, for example, "Trading Friction as a Momentum Killer".)
- The overlapping portfolio approach (monthly formation with six-month holding interval) may be unrealistic with respect to practice.
- The arguably unusual economic/market conditions of 1998-2000 contribute substantially to momentum strategy gross performance.

Originally published at http://www.cxoadvisory.com/16093/momentum-investing/momentum-overview-from-the-discoverers/ on September 9, 2011.

Combining Return Reversal and Industry Momentum

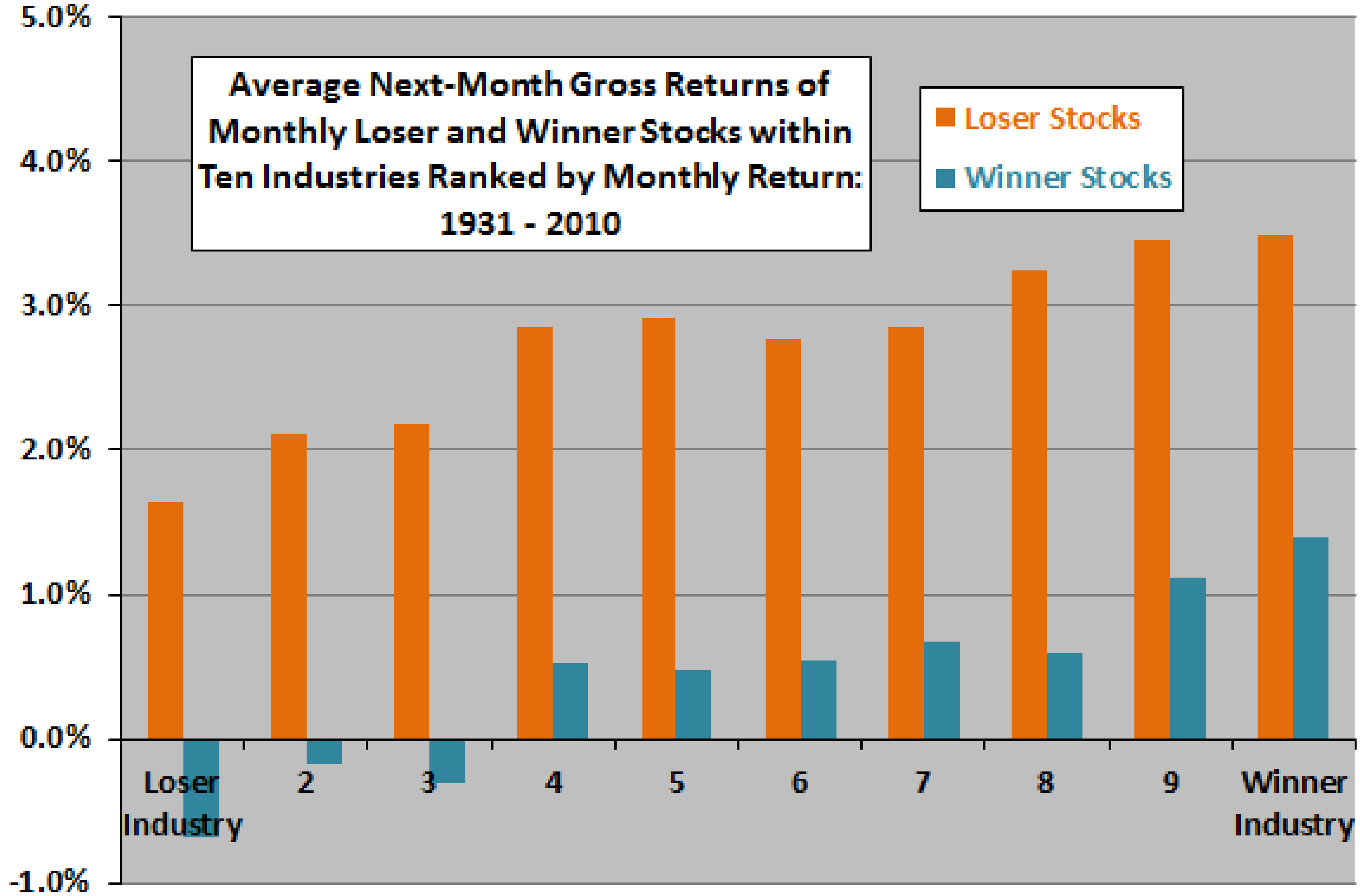
September 2, 2011

Does a strategy of combining monthly individual stock return reversal with monthly industry momentum enhance results compared to the separate strategies. In their August 2011 paper entitled "One-month Individual Stock Return Reversals and Industry Return Momentum", Marc Simpson, Emiliano Giudici and John Emery examine the relationship between individual stock return reversals and industry momentum by considering three strategies: (1) a conventional reversal strategy that each month buys (shorts) individual stock losers (winners); (2) a simple industry momentum strategy that each month buys (shorts) the previous month's winning (losing) industry portfolio; and, (3) a combined reversal-industry momentum strategy that buys (shorts) the losing (winning) stocks within the previous month's winning (losing) industry portfolio. Using monthly returns, SIC codes and the Fama-French definitions for ten industries over the period January 1931 through December 2010 (960 months) , *they find that:*

- Over the entire sample period, confirming prior research:
    - Monthly individual stock winners (losers) have relatively low (high) next-month gross average returns.
    - Monthly industry winners (losers) have relatively high (low) next-month gross average returns.
- The individual stock return reversal effect interacts with the simple industry momentum effect such that shorting past winning stocks within winning industries generates negative returns (see the chart below).
- Over the entire sample period, the combined reversal-industry momentum strategy generates a gross average monthly return of 4.08%, significantly outperforming both the conventional reversal strategy (3.25% per month) and the simple industry momentum strategy (1.59% per month).

The following chart, constructed from data in the paper, summarizes average next-month gross returns of monthly loser and winner stocks within each of ten industries ranked by monthly return over the entire sample period. Results show that:

- The conventional reversal strategy works within each industry at a gross level.
- The gross return to the short side of the conventional reversal strategy is positive (negative) for winning (losing) industries.



In summary, *evidence from simple tests indicates that investors can enhance both a conventional reversal strategy for individual stocks and a simple industry momentum strategy by buying (selling) monthly losing (winning) stocks within the monthly winning (losing) industry.*

Cautions regarding findings include:

- Return calculations are gross, not net. Trading is intensive for the reversal and combination strategies. Incorporation of reasonable trading frictions (generally higher for older subperiods and for shorting) would materially reduce calculated returns.
- Because the combination strategy portfolios are smaller than those of the component strategies, they may exhibit relatively high volatility, working against cumulative return.
- Calculations assume that investors can execute prior-month sorts just before monthly closes, thereby taking responsive positions at these same closes. This assumption may be problematic for some investors from calculation burden and trade execution perspectives. Delaying trades until the next trading day would systematically miss part of the the turn-of-the-month effect.
- Related research finds that performance of a conventional return reversal strategy diminishes at the gross level and disappears at the net level in recent decades. Subperiod robustness tests would be helpful.
- Statistical significance tests assume well-behaved return distributions. To the extent that return distributions are wild, these tests lose meaning.

Originally published at http://www.cxoadvisory.com/15912/technical-trading/combining-return-reversal-and-industry-momentum/ on September 2, 2011.

Combine Long-term SMA, TOTM and Sector Momentum?

July 20, 2011

Based on results from “Simple Sector ETF Momentum Strategy Performance”, “Does the Turn-of-the-Month Effect Work for Sectors?” and “Long-term SMA and TOTM Combination Strategy”, a subscriber proposed: “Have you ever thought of combining the three? When SPY is above a long term average, buy the best performing sector ETF using the TOTM strategy.” To investigate, we consider the nine sector exchange-traded funds (ETF) defined by the Select Sector Standard & Poor’s Depository Receipts (SPDR), all of which have trading data back to December 1998:

Materials Select Sector SPDR (XLB)
Energy Select Sector SPDR (XLE)
Financial Select Sector SPDR (XLF)
Industrial Select Sector SPDR (XLI)
Technology Select Sector SPDR (XLK)
Consumer Staples Select Sector SPDR (XLP)
Utilities Select Sector SPDR (XLU)
Health Care Select Sector SPDR (XLV)
Consumer Discretionary Select SPDR (XLY)

We determine sector momentum based on total return over the past six months (6-1). We define bull-bear stock market state according to whether SPDR S&P 500 (SPY) is above-below its 200-day simple moving average (SMA). We define the turn-of-the-month (TOTM) as the eight-trading day interval from the close five trading days before the first trading day of a month to the close on the fourth trading day of the month. Using daily dividend-adjusted closes for the sector ETFs and SPY from 12/22/98 through 7/11/11 (151 months), *we find that:*

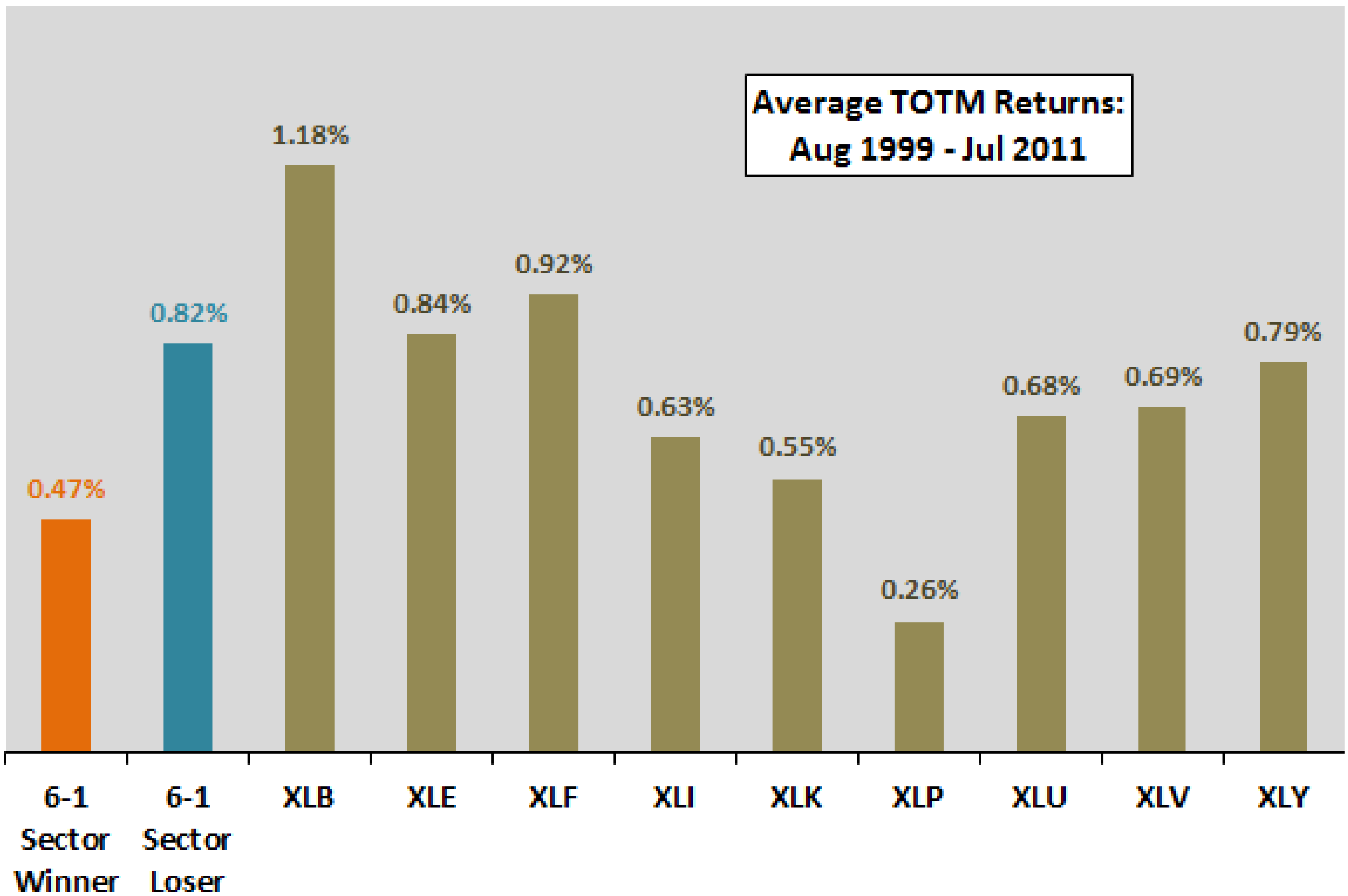
The analyses below make the following assumptions:

- To allow calculation of 6-1 momentum, the first month of TOTM returns is July-to-August 1999.
- Trades occur at the close, with calculation of the 200-day SMA slightly anticipated such that trades coincide with crossing signals.

The following chart compares average TOTM returns for each sector ETF and for prior-month 6-1 momentum winner and loser sectors over the available sample. Notable results are:

- The return is higher for losers than winners (but the standard deviation of TOTM returns is higher for losers).
- The return for past winners is lower than those of all the sector ETFs except one.
- The standard deviation of TOTM returns (not shown) is substantially higher for past losers (4.80%) than for past winners (3.91%). In fact, TOTM return volatility is higher for past losers than for any of the individual ETFs.

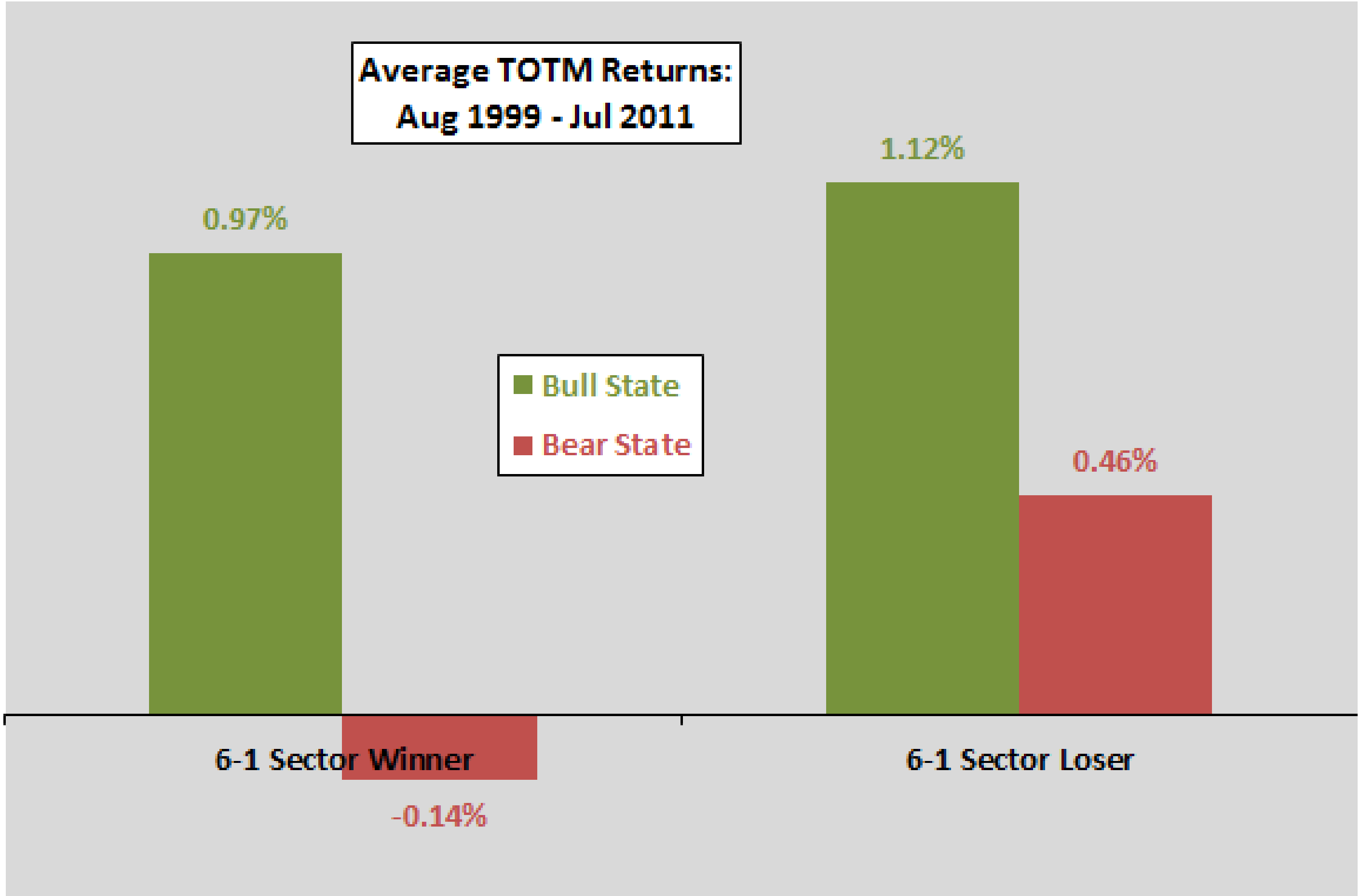
Results suggest that TOTM is more likely connected to reversion (in a risky way) than momentum.



The next chart summarizes average TOTM returns for sector momentum winners and losers by bull and bear stock market states. The average TOTM returns for sector momentum losers are higher than those for winners in both states (but close for the bull state), with both loser and winner average returns higher in the bull state. In the bull (bear) state, the standard deviation of TOTM returns is notably higher (lower) for past winners than past losers.

Again, with TOTM amplification coming from losers, TOTM appears more connected to reversion than momentum.

A possible strategy would be to go with TOTM for sector momentum losers in a bull state and cash in a bear state. However, since the average return for sector momentum losers in the bear state is 0.46%, it might be better to stick with TOTM for sector momentum losers in both bull and bear states.



In summary, *limited evidence from simple tests suggests that the turn-of-the-month effect may be stronger for reversion rather than momentum conditions. In other words, momentum may rob future turn-of-the-month returns.*

Cautions regarding findings include:

- The above analyses do not explicitly combine average return and volatility to construct cumulative trajectories.
- As strategies get more and more complex, there is elevated potential for snooping bias (based on optimization of strategy components).
- Shifting the sector ETF momentum calculation from end of the month (such that there is a nearly one-month delay from signal to next TOTM) to beginning of the TOTM interval may produce different results.

Originally published at http://www.cxoadvisory.com/15060/calendar-effects/combine-long-term-sma-totm-and-sector-momentum/ on July 20, 2011.

Exploiting Momentum While Avoiding Long-term Reversal

June 2, 2011

Is there a way to enhance momentum strategy performance by avoiding stocks about to enter post-momentum, long-term reversals? In the May 2011 version of their paper entitled "Momentum – Reversal Strategy", Hsin-Yi Yu and Li-Wen Chen investigate momentum-reversal trading strategies that buy past winners and sell past losers while seeking to avoid stocks about to reverse. They devise two ways to measure the trend in past stock returns and thereby assess likelihood of return reversal. The comparison method compares geometric mean returns over the past 12 months and n<12 months, hypothesizing that both past winner and past loser stocks with accelerating momentum are more likely to reverse. The alternative convex-concave method graphs geometric mean returns over the past 1 to 12 months versus number of months, hypothesizing that a convex (concave) profile indicates a high (low) probability of reversal for past winners and low (high) probability of reversal for past losers. They test the effectiveness of these two trend measures via five alternative trading strategies that reform portfolios monthly based on different momentum-only and momentum-reversal criteria. Using monthly returns for all NYSE/AMEX and NASDAQ common stocks during 1965 through 2009 (22,421 stocks), *they find that:*

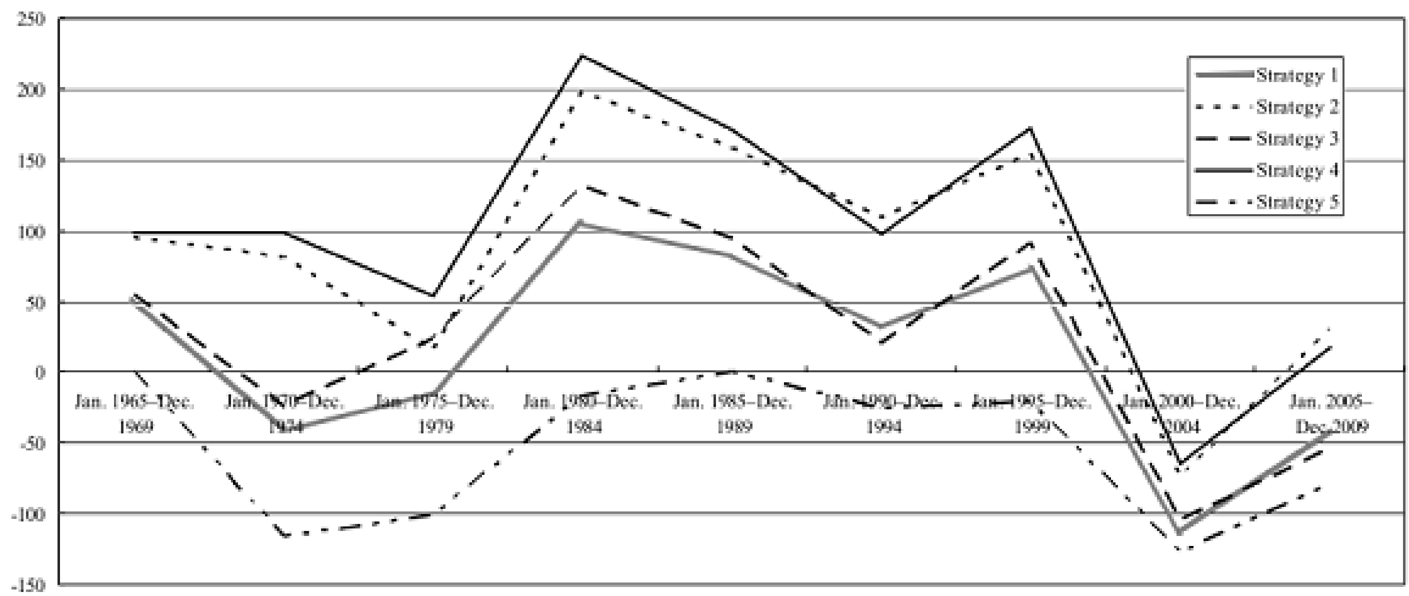
- Gross risk-adjusted (for market, size and book-to-market) returns of momentum-reversal strategies are significantly higher than that of a traditional momentum strategy. Over the entire sample period, annualized average three-factor gross alphas for the momentum-reversal strategies range as high as 26.1% (30.8% excluding Januaries), compared to 6.7% (13.3% excluding Januaries) for the traditional momentum strategy.
- For the comparison method of screening potential reversals:
  - Short comparison intervals (n=1 or n=2 for the past one or two months) are more effective than long intervals.
  - Screening is much more effective for past losers than past winners.
  - Exclusion of Januaries generally enhances returns.
- The convex-concave method screens stocks for potential reversals less ambiguously than the comparison method, requiring no selection of a particular comparison interval. Exclusion of Januaries again enhances returns.
- While the momentum-reversal strategy consistently beats a traditional momentum strategy over consecutive five-year subperiods, it is unprofitable during 2000-2004 and only slightly profitable during 2005-2009 at a gross level (see the chart below).

The following chart, taken from the paper, compares the average monthly three-factor gross alphas (in basis points) of the following five trading strategies based on the convex-concave reversal screening method for each of nine consecutive five-year subperiods:

Strategy 1: The traditional momentum strategy (buy past winners and sell past losers).
Strategy 2: A momentum-reversal strategy that screens out only past losers likely to reverse.
Strategy 3: A momentum-reversal strategy that screens out only past winners likely to reverse.
Strategy 4: The full momentum-reversal strategy that screens out both past losers and past winners likely to reverse.
Strategy 5: A test strategy that screens out both past losers and past winners not likely to reverse.

All portfolios are equally weighted and reformed monthly. Results indicate that:

- The full momentum-reversal strategy consistently beats the traditional momentum strategy (Strategy 4 versus Strategy 1).
- Most of the benefit from the full momentum strategy comes from screening out losers that are about to rebound (Strategy 4 and Strategy 2 are very similar, as are Strategy 1 and Strategy 3).
- Returns for momentum stocks indicated as about to reverse are consistently negative (Strategy 5).
- None of the momentum strategies are attractive over the last decade of the 1965-2009 sample period.



In summary, *evidence indicates that investors may be able to enhance the performance of momentum strategies by using return acceleration metrics to screen out the past winning and losing stocks most susceptible to reversal.*

Cautions regarding findings include:

- As noted in the study, neither momentum nor momentum-reversal strategies are attractive during the 2000s, suggesting the possibility of market adaptation.
- The study ignores trading frictions that would be incurred in implementing the strategies

considered. Momentum strategies tend to generate high portfolio turnover, and trading frictions are high during parts of the sample period.

- The data collection and processing burdens of the momentum-reversal strategies are considerable.

Originally published at http://www.cxoadvisory.com/8218/momentum-investing/exploiting-momentum-while-avoiding-long-term-reversal/ on June 2, 2011.

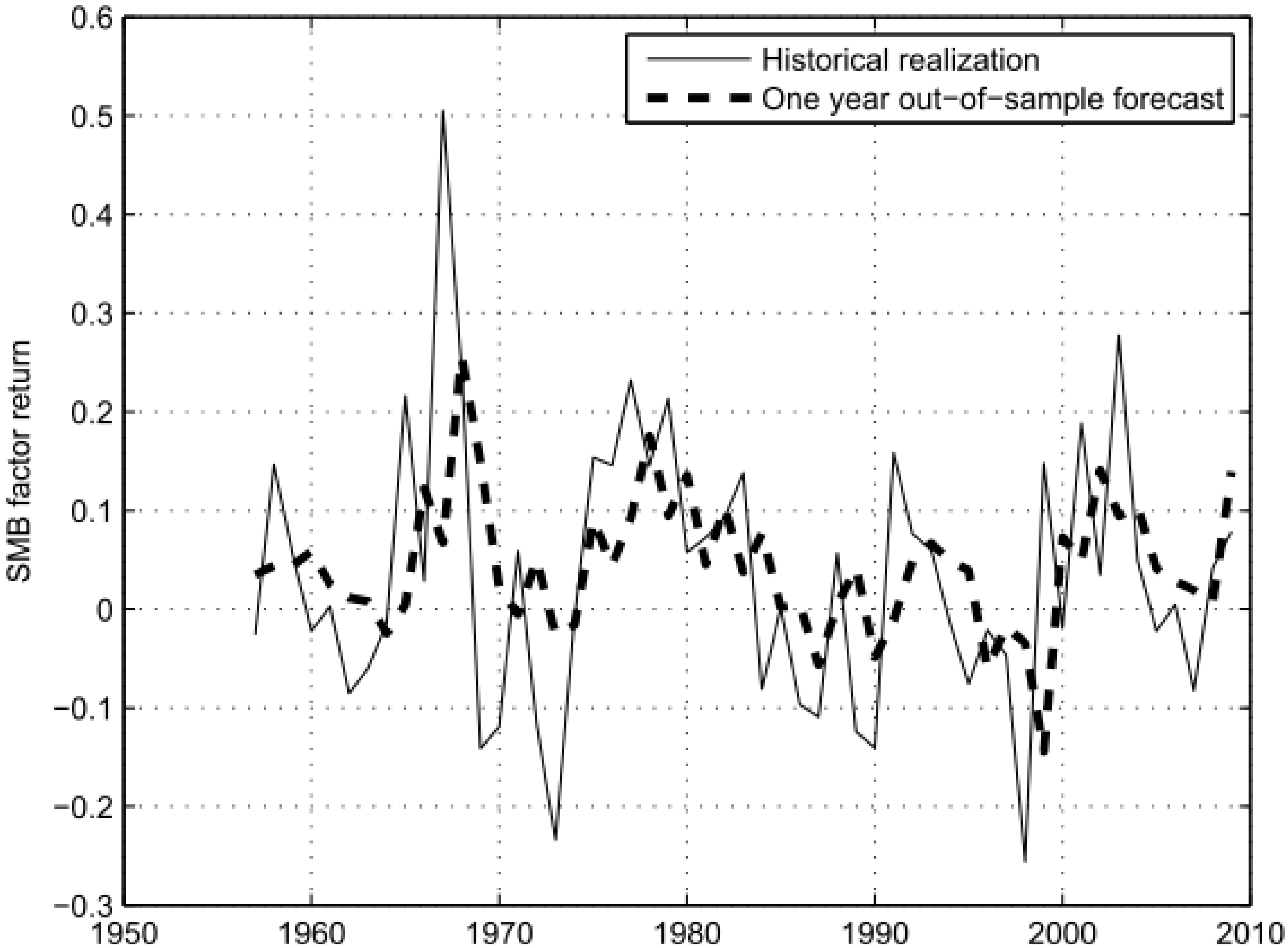
Predicting Variation in the Size Effect

May 18, 2011

Does the size effect vary in a predictable way? In the May 2011 version of his paper entitled "Explaining the Dynamics of the Size Premium", Valeriy Zakamuline investigates relationships between eight market/economic variables and the size effect in U.S. stocks to identify the best model of size effect variation. The eight variables are: (1) stock market return; (2) stock market dividend yield; (3) equity value premium; (4) stock return momentum; (5) default spread (Moody's BAA-AAA corporate bond yield spread); (6) Treasury bill yield; (7) U.S. Treasuries term premium (30-year bond yield minus one-month bill yield); and, (8) inflation rate. He then tests the exploitability of the best model via a strategy that switches between small-capitalization and large-capitalization stocks out of sample based on inception-to-date historical data. Using annual data for the eight potentially predictive variables and annual and monthly data for the magnitude of the size effect among NYSE, AMEX and NASDAQ stocks as available over the period 1927 through 2009 (83 years), *he finds that:*

- The size premium tends to emerge as the term premium increases and after negative market returns (during "bad times"). Moreover, the size effect tends to persist (exhibits momentum).
- A strategy that each year allocates all funds to the smallest tenth of market capitalizations on a value-weighted basis when the inception-to-date combination of lagged market returns and lagged size effect predicts a positive size effect, and otherwise allocates all funds to the largest tenth of market capitalizations, generates an economically and statistically significant gross three-factor (adjusting for market, size and book-to-market) monthly alpha during 1957-2009.
  - The magnitude of this alpha is roughly half that based on perfect foresight of the size effect over the test period.
  - The Sharpe ratio for the strategy is substantially greater than that for consistently holding either the smallest or largest tenth of market capitalizations over the test period.
  - Results generally hold both for the entire 1957-2009 out-of-sample test period and for a 1972-2009 subperiod.
  - When adjusted for a momentum factor, the strategy exhibits a gross alpha that is economically but not statistically significant.
  - Trading frictions for the strategy are arguably immaterial because switching is infrequent (due to size effect persistence), though there would be annual trading frictions from stocks entering and leaving the smallest and largest tenths of market capitalizations.

The following chart, taken from the paper, portrays rolling one-year forecasts of the size effect return during a 1957-2009 out-of-sample test period based on lagged size effect magnitude and lagged stock market returns. The initial 1957 prediction derives from data for 1927-1956, with one year of historical data added for each iterative prediction. The correlation between actual and predicted size effect returns over the entire test period is 0.347 (R-squared statistic 0.12, indicating that the prediction explains 12% of the variation in actual returns). The R-squared statistic for the 1972-2009 subperiod is 0.17.



In summary, *evidence indicates that investors may be able to time the size effect in the U.S. stock market based on its positive relationship with the lagged magnitude of the size effect itself and its negative relationship with lagged stock market returns.*

The fact that the size effect emerges during bad times suggests a connection to lagged stock market volatility.

Cautions regarding findings include:

- The sample is not long when defined in terms of numbers of "bad times" and "good times."
- Investigating the explanatory powers of many variables within a single data set (at both individual researcher and community levels) introduces data snooping bias, thereby overstating the power of the best model.
- Even though switching frequency is low at for the strategy described above, trading

frictions during parts of the out-of-sample test (especially for small-capitalization stocks) would be very large compared to modern values, especially for investors with limited funds (implying many small positions). In other words, it is not obvious that trading frictions are immaterial.
- Statistical significance tests apparently assume tame variable distributions. To the extent that actual distributions are wild, these tests lose power.

See "Doing Momentum with Style (ETFs)" and "Measuring the Size Effect with Capitalization-based ETFs" for explorations of related concepts accessible to many individuals via exchange-traded funds.

Originally published at http://www.cxoadvisory.com/13975/size-effect/predicting-variation-in-the-size-effect/ on May 18, 2011.

Which Kind of (ETF) Momentum Is Best?

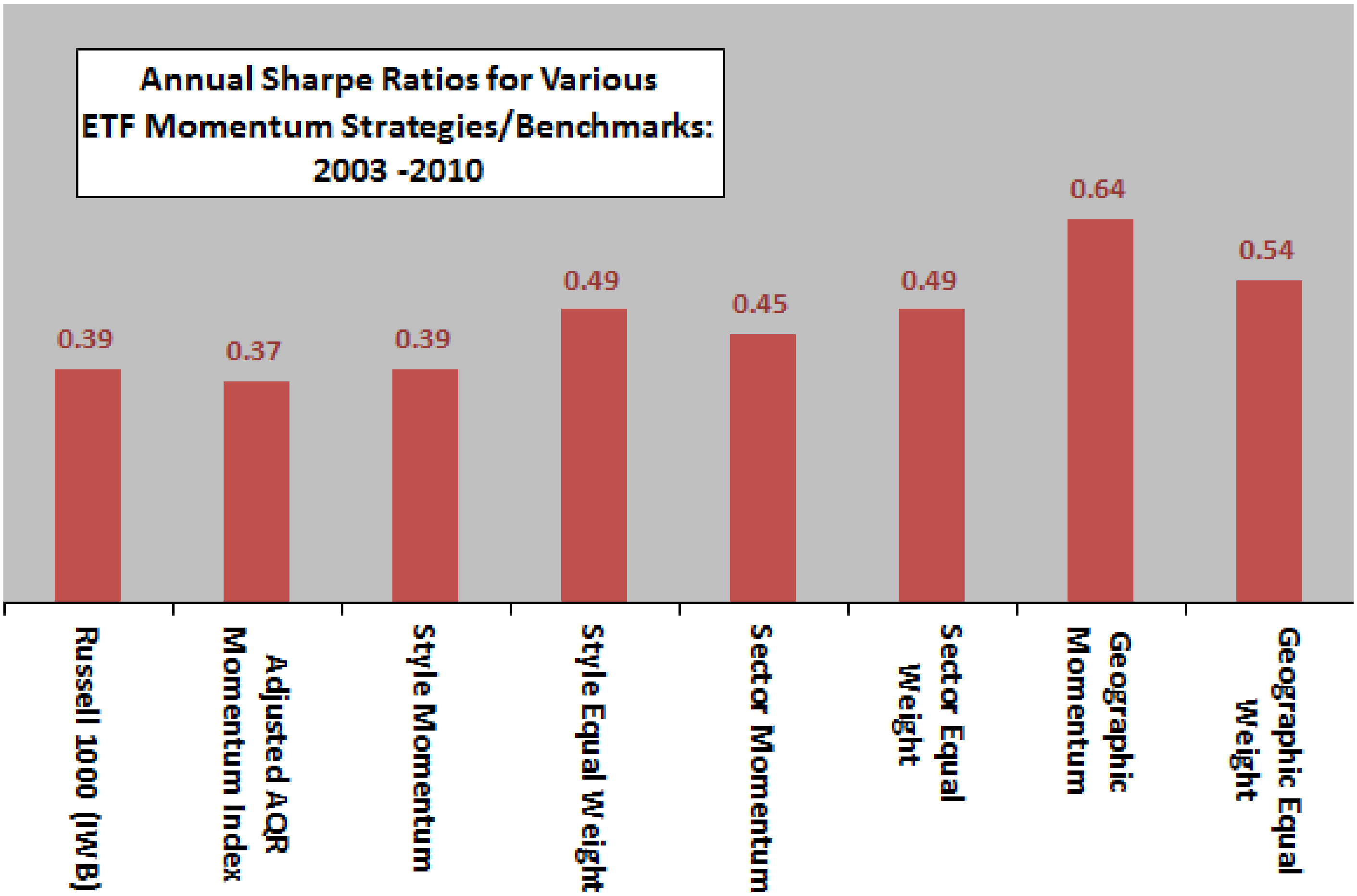
May 4, 2011

When implemented via exchange-traded funds (ETF), does an equity sector momentum strategy beat an equity style momentum strategy? How do these approaches compare to a geographic equity momentum strategy? In his paper entitled "Optimal Momentum", runner-up for the 2011 Wagner Award presented by the National Association of Active Investment Managers, Gary Antonacci uses ETFs to compare style, sector and geographic momentum strategies. He uses a six-month ranking period to select the top two of six iShares value-growth-size ETFs, the top three of nine SPDR sector ETFs and the top two of four iShares region/country ETFs each month, with a 0.2% per fund switching friction. In addition, he experiments with adding short-term and intermediate-term Treasury ETFs and then gold to the geographic momentum ranking process. His benchmarks are the Russell 1000 ETF (IWB), the AQR Momentum Index (adjusted by debiting an estimated annual trading friction of 0.7%) and equally weighted portfolios of the ETF groups (rebalanced monthly). Using eight years of monthly ETF prices (2003 through 2010) and 34 years of related monthly index levels, *he concludes that:*

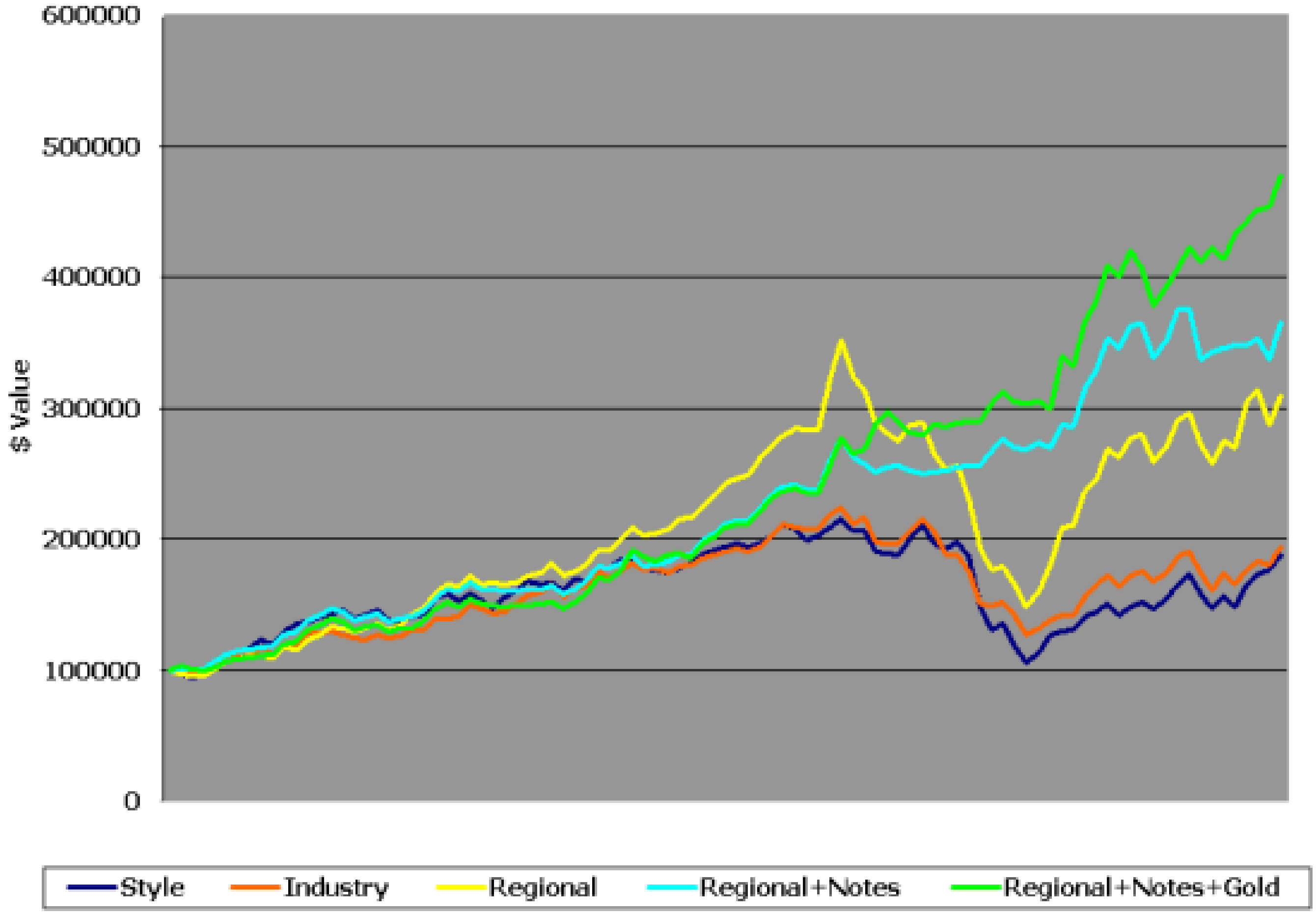
- Average annual trading frictions vary from 0.39% to 0.53% across momentum strategies.
- The geographic momentum strategy generates the highest Sharpe ratio among the basic ETF momentum strategies and benchmarks. The style and sector momentum strategies underperform their equal-weighted counterparts (see the first chart below).
- Adding short-term and intermediate-term Treasury ETFs to the geographic momentum strategy boosts Sharpe ratio from 0.64 to 1.12 and dramatically reduces maximum drawdown.
- Further adding gold to the geographic-Treasury ETF momentum strategy boost the Sharpe ratio to 1.31 (see the second chart below).
- A robustness test applied to related indexes with no trading frictions over the period 1977-2010, and subperiods 1977-1993 and 1994-2010, indicates that a geographic-Treasuries-gold momentum strategy substantially outperforms a corresponding equal-weighted strategy in terms of Sharpe ratio.

The following chart, constructed from data in the paper, summarizes annual Sharpe ratios for the various ETF momentum and benchmark strategies as specified over the 2003-2010 sample period. Results suggest that:

- The adjusted AQR Momentum Index does not outperform buying and holding IWB.
- Sector momentum beats style momentum.
- The style and sector momentum strategies offer little or no advantage relative to buying and holding IWB, and both underperform corresponding equal weighting strategies.
- The geographic momentum strategy performs best (but, not shown, experiences the largest maximum drawdown).



The next chart, taken from the paper, translates the Sharpe ratios for the six ETF momentum strategies specified above (with "Industry" meaning sector) into cumulative performance trajectories of $100,000 initial investments over the 2003-2010 sample period. Results show that adding Treasury ETFs and gold to the geographic momentum strategy considerably dampens volatility.



In summary, *evidence from a short recent sample suggests that a geographic equity momentum strategy beats equity style and sector momentum strategies, and that adding Treasury ETFs and gold to the geographic momentum mix substantially boosts performance.*

Cautions regarding conclusions include:

- As summarized above, the "industry" momentum strategy described in the paper is a sector momentum strategy. Industry segmentation of firms is typically much finer than sector segmentation.
- The basic sample period is very short for reliable inference, consisting of only 16 independent six-month ETF ranking intervals.
- Experimentation with a variety of strategies on the same/overlapping/correlated data introduces data snooping bias, thereby likely overstating the performance of the best strategy. This bias grows with the number of alternatives considered and is especially pernicious for a short sample period.
- Results may include borrowed data snooping bias from selection of a six-month ranking interval. "Simple Sector ETF Momentum Strategy Robustness/Sensitivity Tests" finds that sector ETF momentum strategy performance is inconsistent for different momentum ranking intervals, with a six-month interval perhaps lucky.
- The indexes used in the 34-year robustness test represent idealized (frictionless) market environments. The frictions associated with implementing indexes as portfolios vary considerably over time and across indexes and may be very large over parts of the

sample period, undermining confidence that findings for indexes translate to real trading.

- The statistical interpretations assume that asset return distributions are tame (such as the Gaussian or normal distribution). To the extent that actual distributions are wild, these interpretations lose meaning.

Compare results with those presented in "Simple Sector ETF Momentum Strategy Performance" (and associated robustness/refinement testing) and "Doing Momentum with Style (ETFs)". These analyses involve somewhat longer sample periods and pick one sector/style winner each month. The former finds that adding a long-term simple moving average signal substantially enhances returns. The latter study finds that style momentum outperforms sector momentum.

Originally published at http://www.cxoadvisory.com/13774/momentum-investing/which-kind-of-etf-momentum-is-best/ on May 4, 2011.

Equity Investing Based on Liquidity

April 29, 2011

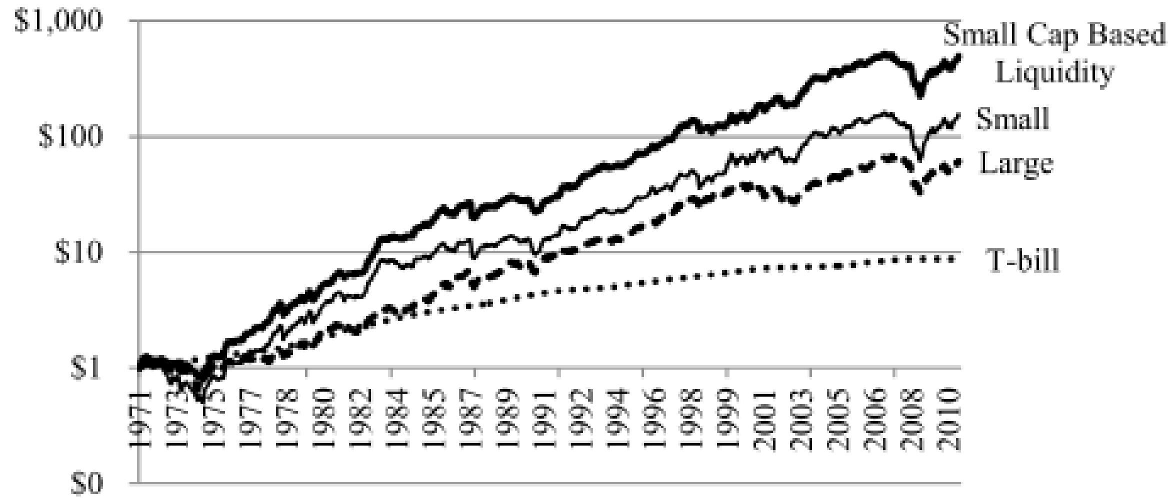
Is the variation of individual stock returns with liquidity a sound investment foundation? In the April 2011 version of their paper entitled "Liquidity as an Investment Style", Roger Ibbotson, Zhiwu Chen and Wendy Hu examine the viability and distinctiveness of a liquidity investment style and investigate the portfolio-level performance of liquidity in combination with size, value and momentum investment styles. They define liquidity as annual turnover, number of shares traded divided by number of shares outstanding, a metric fairly independent of market capitalization. They hypothesize that stocks with relatively low (high) turnover tend to be near the bottom (top) of their ranges of expectation. Their liquidity style thus overweights (underweights) stocks with lower (higher) annual turnover. Using monthly data for the 3,500 U. S. stocks with the largest market capitalizations (with some screening for price, market capitalization, stock type and data availability) over the period 1972-2010, *they find that:*

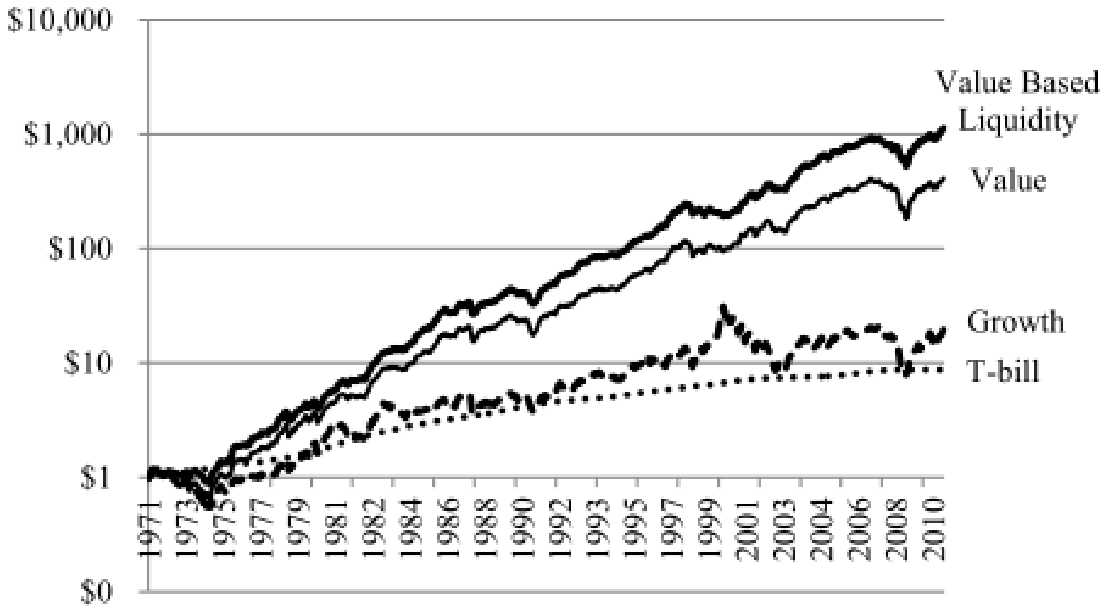
- Annual independent sorts of stocks into four ranks of market capitalization, earnings-to-price ratio (E/P), past 12-month returns and annual turnover indicate that:
    - The liquidity effect persists after controlling for the size effect but decreases systematically as size increases. Within the fourth of stocks with the smallest (biggest) market capitalizations, the intersecting low-liquidity group earns a geometric mean annual return of 18.2% (12.5%) compared to 6.2% (9.9%) for the intersecting high-liquidity group.
    - The liquidity effect is essentially independent of the value premium. Within the fourth of stocks with the highest (lowest) E/P, the intersecting low-liquidity group earns a geometric mean annual return of 20.8% (11.9%) compared to 12.5% (3.9%) for the intersecting high-liquidity group.
    - The liquidity effect is largely independent of the momentum effect. Within the fourth of stocks with the highest (lowest) momentum, the intersecting low-liquidity group earns a geometric mean annual return of 17.4% (14.3%) compared to 11.0% (5.6%) for the intersecting high-liquidity group.
- In general, volatilities (standard deviations) of low-liquidity portfolios are lower than those of high-liquidity portfolios.
- Separate regression testing of liquidity versus a four-factor (market, size, book-to-market, momentum) model of stock returns indicates that the liquidity premium relates negatively to market returns and size, and positively to value and momentum. However, liquidity alpha is positive and significant.
- Results support an interpretation that the market offers a long-term premium to those buying illiquid stocks, with the premium realized slowly as liquidities of individual stocks revert to respective means.

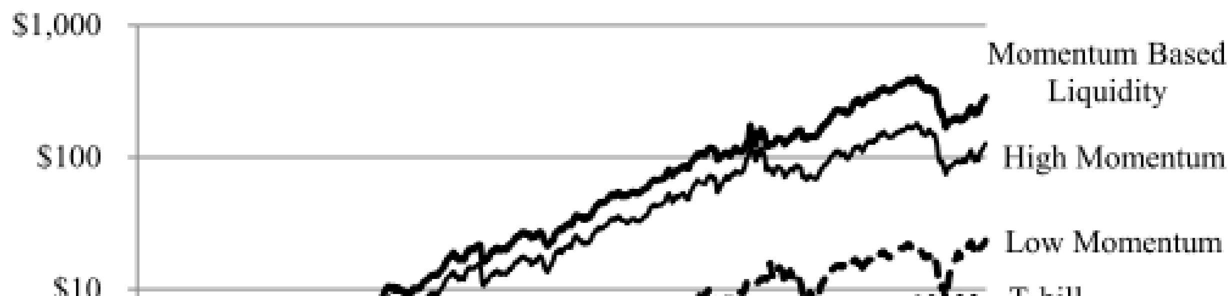
The following charts, taken from the paper, compare cumulative gross values of $1 initial investments in liquidity enhancements of size, value and momentum portfolios over the entire sample period. The combinations are the annually reformed:

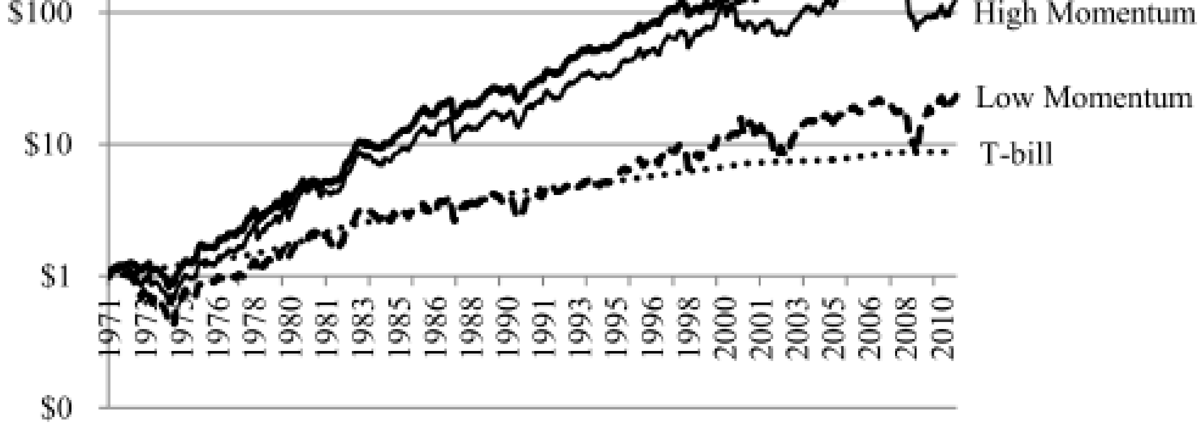
- Intersection of smallest fourth of stocks and least liquid fourth of stocks (upper chart).
- Intersection of the fourth of stocks with the highest E/P and least liquid fourth of stocks (middle chart).
- Intersection of fourth of stocks with the highest 12-month momentum and least liquid fourth of stocks (lower chart).

In all three cases, combination portfolios outperform size, value and momentum alone on a gross basis.









In summary, *evidence indicates that long-term investors may be able to boost returns by incorporating a liquidity style into stock selection. Portfolios that are long (short) the liquidity-other factor combination with the best (worst) returns offer enhanced hedging approaches.*

Cautions regarding findings include:

- Reported returns are gross, not net. Incorporating reasonable trading frictions (which vary considerably over the sample period and at some times are very high) would depress results. Also, since bid-ask spreads relate positively to share turnover, trading frictions tend to be higher for illiquid stocks. The low (annual) portfolio reformation frequency mitigates this concern. Results across subperiods (not available) would help show how trading friction relates to gross profitability.
- Implementing a combination strategy may require considerable capital to establish enough positions to achieve outcome reliability.

Originally published at http://www.cxoadvisory.com/8377/size-effect/equity-investing-based-on-liquidity/ on April 29, 2011.

12-month High Effect for Sectors?

April 19, 2011

“The Industry 52-week High Effect” summarizes findings that the 52-week high effect, the future outperformance (underperformance) of stocks currently near their respective 52-week highs (lows), is stronger and more consistent for 20 industries than for individual stocks. Do findings apply to equity sectors that are somewhat broader than the 20 industries? Specifically, might such a strategy outperform past six-month return when applied to the following nine sector exchange-traded funds (ETF) defined by the Select Sector Standard & Poor’s Depository Receipts (SPDR), all of which have trading data back to December 1998:

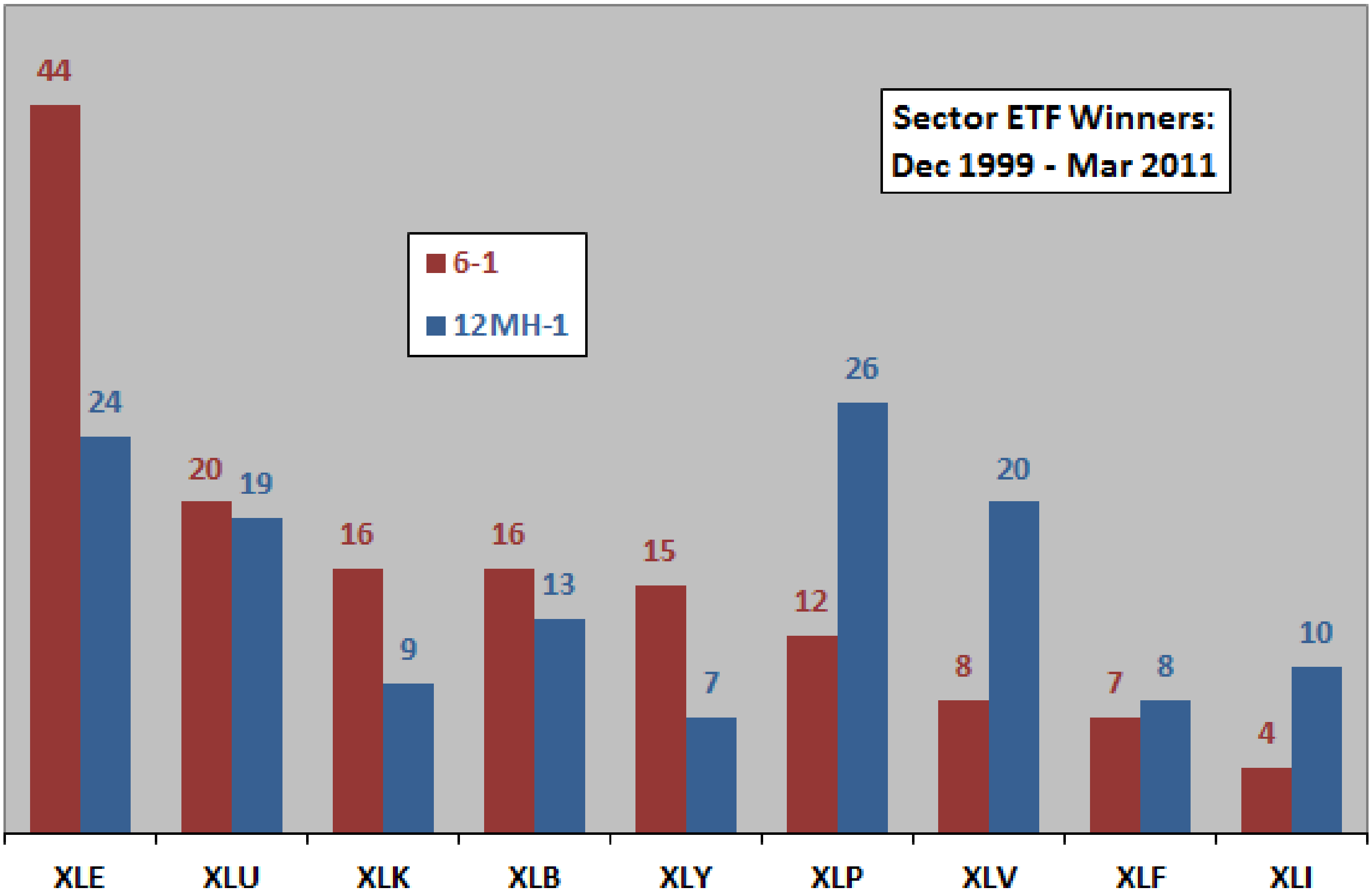
Materials Select Sector SPDR (XLB)
Energy Select Sector SPDR (XLE)
Financial Select Sector SPDR (XLF)
Industrial Select Sector SPDR (XLI)
Technology Select Sector SPDR (XLK)
Consumer Staples Select Sector SPDR (XLP)
Utilities Select Sector SPDR (XLU)
Health Care Select Sector SPDR (XLV)
Consumer Discretionary Select SPDR (XLY)

To check, we consider three strategies based on closeness of each sector ETF to its 12-month high, defined as ratio of monthly close to highest monthly close over the prior 12 months. The three strategies are to: (1) allocate all funds each month to the sector ETF closest to its 12-month high at the end of the preceding month (12MH-1); (2) allocate all funds each month to the sector ETF closest to its 12-month high at the end of the month before the preceding month (12MH-1;1); and, (3) allocate all funds each quarter to the sector ETF closest to its 12-month high at the end of the month before the end of the quarter (12MH-3;1). Strategy (2) addresses the concern that a sector ETF surging toward a 12-month might experience some reversion the next month, and strategy (3) addresses the concern (based on the methodology in “The Industry 52-week High Effect”) that the effect materializes over several months. For comparison, we include the strategy of monthly allocation to the sector ETF with the highest total return over the past six months (6-1). Using monthly dividend-adjusted closing prices for the nine sector ETFs and S&P Depository Receipts (SPY) over the period December 1998 through March 2011 (148 months), we find that:

Note that the three test strategies require use of the first 12 months of the sample for calculating closeness to 12-month highs and month 13 as a skip-month, so return calculations start in month 14 of the sample.

The following chart compares the distributions of 136 sector ETF winners for the benchmark 6-1 momentum strategy and the 12MH-1 strategy over the available sample period. The distributions are quite different, with the 12MH-1 strategy switching more frequently (87 versus 56 times).

How do the 12-month high strategies translate into cumulative returns?



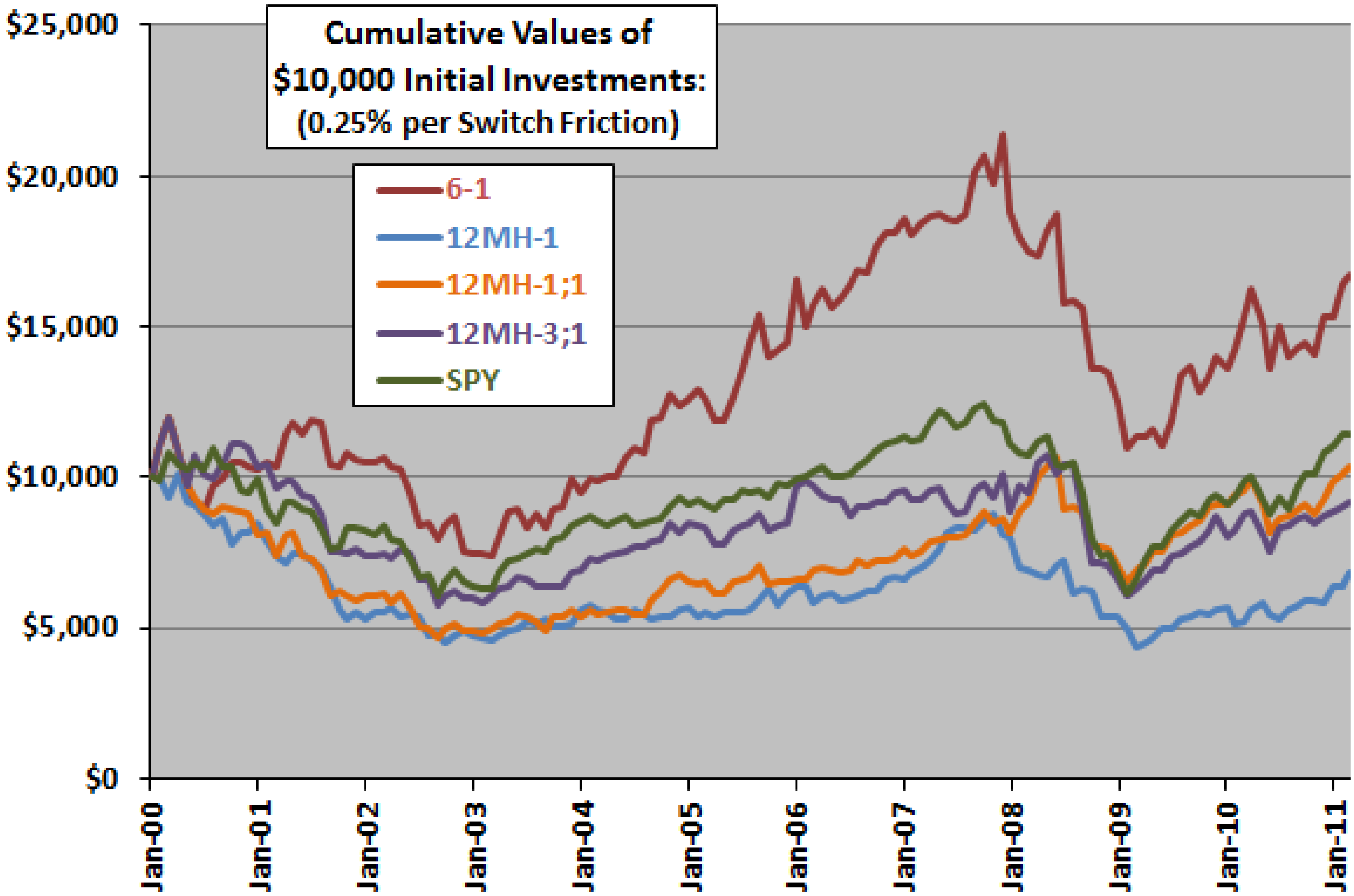
The next chart compares the cumulative values of $10,000 initial investments in the three 12-month high strategies, the benchmark 6-1 strategy and SPY over the available sample period. Calculations derive from the following assumptions:

- Reallocate at the close on the last trading days of signaled months/quarters (assume signals can be calculated just before the close).
- Trading (switching) friction is 0.25% of the balance whenever there is a change in ETF.
- Ignore any tax implications of trading.

At the assumed level of switching friction, all three 12-month high strategy variations underperform the benchmark 6-1 strategy and buying and holding SPY. Setting trading friction to zero enables the 12MH-1;1 strategy to outperform SPY modestly part of the time, but the other two 12-month high strategies still generally underperform SPY.

Average net monthly returns for the 12MH-1, 12MH-1;1 and 12MH-3;1 strategies are-0.14%, 0.15% and 0.09%, respectively, compared to 0.56% for the benchmark 6-1 strategy and 0.21%

for SPY. The 6-1 strategy (SPY) has a higher (lower) standard deviation of net monthly returns than do the 12-month high strategies.



In summary, *the simple sector ETF 12-month high strategies have generally underperformed a simple sector ETF momentum strategy and the broad stock market over the past 12 years.*

Reasons results do not agree with cited research may be that:

- Sample size is small (just 12 independent 12-month ranking intervals), and the poor performance of the 12-month high strategies may be anomalous.
- Nine sectors may not be sensitive enough to capture effects found for 20 industries in the cited research. However, it seems that the simplified approach should find some benefit.
- Measurement of highs relative to the previous 12 monthly closes (rather than the highest intraday value over the past 52 weeks) may not be sensitive enough to find the “high” effect. However, it seems that the simplified approach should find some benefit.

Originally published at http://www.cxoadvisory.com/13463/technical-trading/12-month-high-effect-for-sectors/ on April 19, 2011.

The Industry 52-week High Effect

April 18, 2011

Are 52-week highs and lows useful equity price momentum indicators at the industry level? In their March 2011 paper entitled "Industry Information and the 52-Week High Effect", Xin Hong, Bradford Jordan and Mark Liu compare the 52-week high effect for industries to that for individual stocks. This effect consists of the future outperformance (underperformance) of stocks currently near their respective 52-week highs (lows). Using monthly closes and rolling 52-week (intraday) highs for all stocks listed on NYSE, AMEX and NASDAQ and 20 value-weighted industry indexes constructed from SIC codes for these firms over the period July 1963 through 2009, *they find that:*

- Comparing 52-week high effects for industries and individual stocks:
  - A hedge strategy that each month buys (sells) the equally weighted stocks in the top (bottom) six of 20 industries ranked by ratio of current index level to 52-week index high and holds for six months generates an average gross monthly return of 0.60% over the entire sample period.
  - For comparison, a strategy that each month buys (sells) the equally weighted 30% of individual stocks closest to (farthest from) their respective 52-week highs and holds for six months generates an average monthly gross return of 0.43% over the same period.
- The contribution from the long side of the industry strategy is about twice as big as that from the short side.
- Excluding January sightly (dramatically) increases profitability for the 52-week high strategy as applied to industries (individual stocks). Conversely, the strategy generates an average return of -0.94% (-7.62%) in January for industries (individual stocks).
- The 52-week high strategy works best among stocks with relatively high industry return correlations and betas (stocks more affected by industry factors) and does not work among stocks with low industry return correlations and betas.
- Sophisticated institutional investors, unlike typical investors, buy (sell) stocks whose prices are close to (far from) 52-week highs.
- Results are mostly robust over subperiods, to exclusion of the Internet bubble and recent financial crisis, for 3-month and 12-month holding intervals, and after controlling for common equity return factors (market, size, book-to-market, momentum).

In summary, *evidence indicates that investors may be able to exploit the 52-week high strategy more profitably and consistently for industries than for individual stocks.*

Cautions regarding findings include:

- Reported returns are gross, not net. Including reasonable trading frictions would dent

returns, but the relatively long six-month holding period mitigates.
- Forming the portfolios tested economically requires a large amount of capital.
- Statistical significance tests assume tame return distributions. To the extent that actual distributions are wild, the meaning of the tests breaks down.

See “The 52-Week High as a Momentum Indicator for Individual Stocks” for findings of the key predecessor study.

Originally published at http://www.cxoadvisory.com/13447/technical-trading/the-industry-52-week-high-effect/ on April 18, 2011.

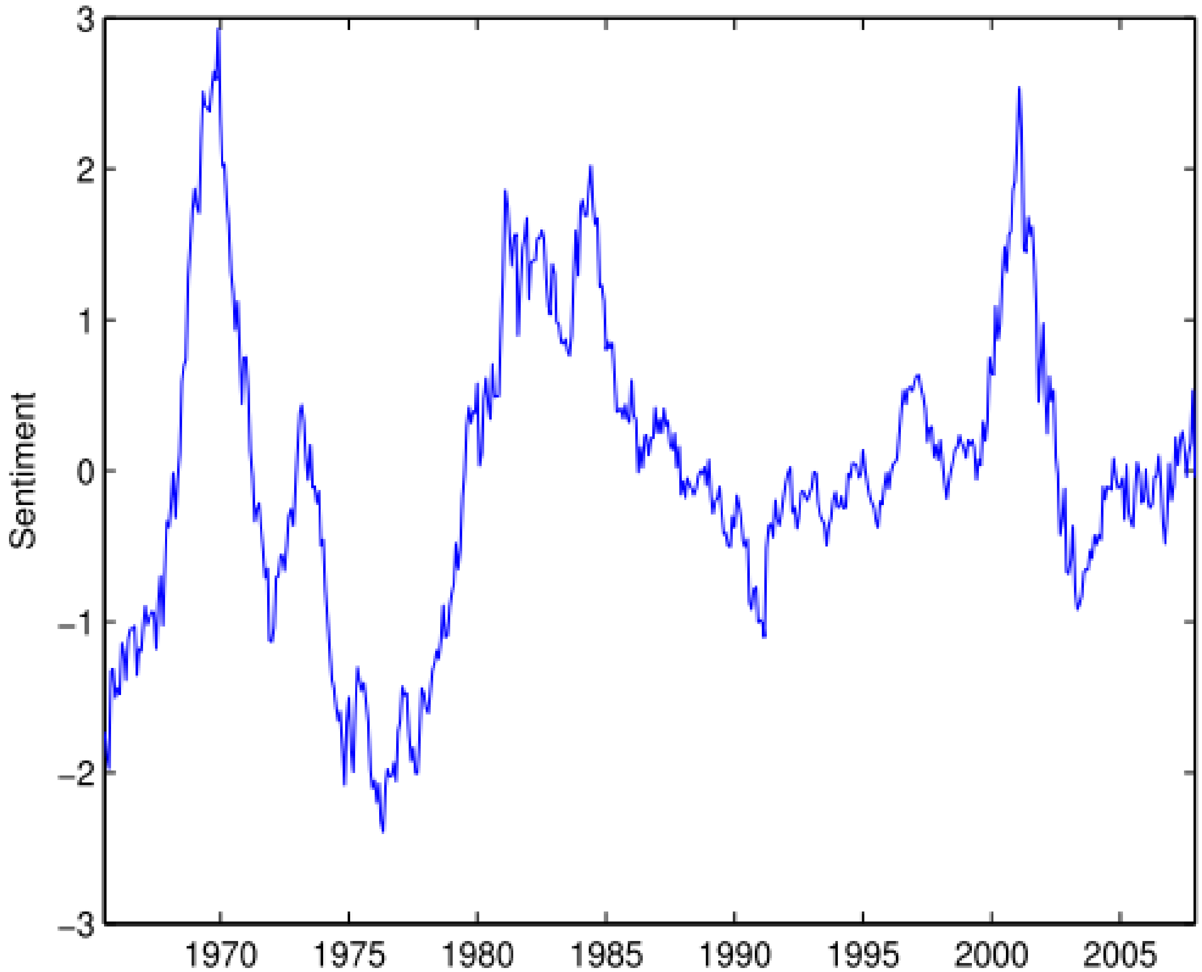
Interaction of Investor Sentiment and Stock Return Anomalies

April 4, 2011

Does aggregate investor sentiment affect the strength of well-known U.S. stock return anomalies? In their January 2011 paper entitled "The Short of It: Investor Sentiment and Anomalies", Robert Stambaugh, Jianfeng Yu and Yu Yuan explore the interaction of aggregate investor sentiment with 11 cross-sectional stock return anomalies. Their approach reflects expectations that: (1) overpricing of stocks is more common than underpricing due to short-sale constraints; and, (2) a high sentiment level amplifies overpricing. Specifically, they consider the effect of investor sentiment on hedge portfolios that are long (short) the highest(lowest)-performing) value-weighted deciles of stocks sorted on: financial distress (two measures), net stock issuance, composite equity issuance, total accruals, net operating assets, momentum, gross profit-to-assets, asset growth, return-on-assets and investment-to-assets. They use a long-run sentiment index derived from principal component analysis of six sentiment measures: trading volume as measured by NYSE turnover; the dividend premium; the closed-end fund discount; the number of and first-day returns on Initial Public Offerings; and, the equity share in new issues. They measure anomaly alphas relative to the three-factor model (adjusting for market, size, book-to-market). Using monthly sentiment and stock return anomaly data as available over the period July 1965 through January 2008, *they find that:*

- All 11 hedge portfolios produce significantly positive average gross excess returns (relative to one-month Treasury bills) and gross three-factor alphas. The average monthly gross alpha for anomaly portfolios weighted equally is 0.87%, ranging from 0.43% for composite equity issuance to 1.77% for momentum.
- All anomalies are stronger following relatively high levels of sentiment. On average across anomalies, 70% of hedge portfolio gross alpha occurs in months following above-median sentiment. Time-series regressions confirm that anomaly alphas relate positively to investor sentiment.
- Anomaly amplification comes from the short side. On average across anomalies, 78% of the gross alpha from short sides of hedge portfolios occurs in months following above-median sentiment. Time-series regressions confirm that short-side returns relate negatively to investor sentiment.
- Conversely, there is no relationship between long-side alphas and investor sentiment. On average across anomalies, the difference in long-side monthly alpha after high and low sentiment months is only 0.04%.
- Results also generally hold for a processed version of the University of Michigan Consumer Sentiment Index.

The following chart, taken from the paper, plots the aggregate investor sentiment index used in the study over the sample period. The sentiment index is a dynamic distillation of the six raw sentiment measures identified above, adjusted for several macroeconomic indicators and a dummy variable for NBER recessions. Note that such variables (especially NBER recession dates) are not known in real time, indicating look-ahead bias. Moreover, the study apparently uses the overall sample median as a high-low threshold for sentiment. Because of the wide swings in sentiment, the medians for exploitable to-date and rolling historical data are often very different from the overall sample median.



In summary, *evidence suggests that investors may be able to enhance results for hedge strategies that exploit common stock return anomalies by concentrating on intervals when aggregate investor sentiment is high.*

Cautions regarding these findings include:

- As noted above, there appear to be two sources of look-ahead bias in the aggregate investor sentiment index used in the study. Eliminating this bias by using only real-time data may substantially affect findings.
- Reported returns and alphas are gross, not net. Including reasonable trading frictions for monthly portfolio rebalancing would likely degrade anomaly profitabilities substantially. Incremental trading to incorporate investor sentiment signals would add to trading frictions. Also, trading frictions may be systematically related (via liquidity) to investor sentiment such that trading is more costly when sentiment is high.

- The sentiment indexes used are complex or involve some complex adjustments. It would be interesting to know whether findings for some simpler real-time measure of aggregate investor sentiment are exploitable.
- It would be interesting to see how the 2008-2009 financial crisis affects findings.

See "Investor Sentiment and Returns for Different Types of Stocks" for a similar study considering other firm characteristics.

Originally published at http://www.cxoadvisory.com/12966/fundamental-valuation/interaction-of-investor-sentiment-and-stock-return-anomalies/ on April 4, 2011.

Interactions of Momentum, Valuation and Idiosyncratic Volatility

March 30, 2011

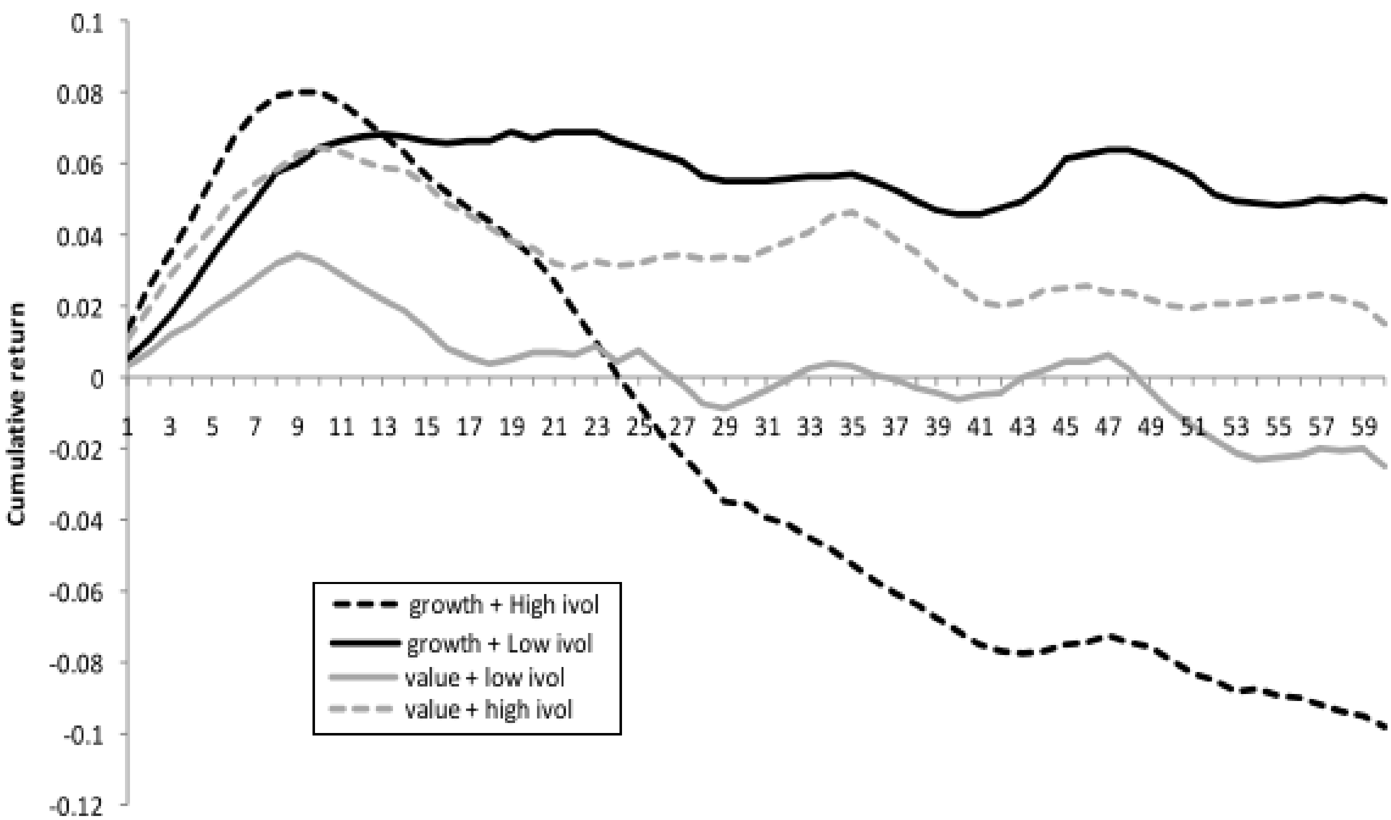
For what kind of stocks does momentum work best? In his March 2011 paper entitled "Growth Options, Idiosyncratic Volatility and Momentum", Umut Celiker investigates the interactions among valuation (market to-book ratio, arguably a proxy for firm growth opportunities), valuation uncertainty (idiosyncratic volatility) and stock price momentum. For calendar-time analysis, he ranks stocks each month into quintiles by past six-month return, with a skip-month, and holds an equal-weighted hedge portfolio that is long the top (winner) quintile and short the bottom (loser) quintile for the next six months. For event analysis, he extends the holding interval to 60 months to explore momentum persistence/reversal. He computes stock idiosyncratic volatility relative to the S&P 500 Index over the prior 36 months. He defines the up (down) market state as the top 80% (bottom 20%) of months based on 60-month past value-weighted market returns averaged for each of the lagged six months. Most analysis focuses on the up market state. Using monthly firm accounting and stock price data for a broad sample of U.S. stocks over the period 1965 to 2008, *he finds that:*

- Over the entire sample period, the specified long-short momentum strategy generates an average monthly gross return of 0.86%, with three-factor (market, size, book-to-market) gross alpha 0.32%.
- Momentum hedge portfolio profitability at a six-month horizon:
  - Is stronger in the up market state. The average monthly gross return during the up (down) market state is 0.95% (0.49%).
  - Is significant for all market-to-book ratio quintiles, strengthening as the ratio increases. The average monthly gross return is 0.70% (1.19%) for value (growth) firms, with the relatively strong (weak) performance of value (growth) losers driving the difference. During the down market state, momentum is significant only for value stocks.
  - Increases with idiosyncratic volatility. The average monthly gross return is 0.43% (1.17%) for low (high) idiosyncratic volatility.
- Cumulative momentum profits increase during the first year after portfolio formation and then reverse during years two through five for both value and growth stocks, with much of the reversal occurring in years two and three (-8.68% for growth stocks).
- Combining momentum, market-to-book and idiosyncratic volatility and past returns, using division by terciles (thirds) rather than quintiles to maintain subsample sizes (see the chart below):
  - Growth stock losers with high idiosyncratic volatilities are the principal drivers of both intermediate-term momentum and long-term reversal.
  - Growth stock winners (losers) contribute more to momentum profitability for low (high) idiosyncratic volatility.

- For low idiosyncratic volatility, growth stock momentum profits do not reverse over the next four years. For example, the average cumulative gross return of growth stocks over these four years is -2.08% (-17.2%) for low (high) idiosyncratic volatility.
- While increasing the holding period to 12 months eliminates the difference in momentum returns between value and growth stocks for high idiosyncratic volatility, growth still beats value by 0.37 % per month for low idiosyncratic volatility.

The following chart, taken from the paper, plots average cumulative momentum hedge returns as specified above for equal-weighted portfolios of different combinations of valuation and idiosyncratic volatility over the 60 months after formation during 1965-2008. Results indicate that:

- Growth stocks with high idiosyncratic volatility offer the largest momentum profitability, but suffer severe long-term reaction.
- Growth stocks with low idiosyncratic volatility offer moderate momentum profitability, with little or no long-term reversal.
- Value stocks with low idiosyncratic volatility offer weak momentum profitability, with long-term reversal.
- Value stocks with high idiosyncratic volatility offer moderate momentum profitability, with only partial long-term reversal.



In summary, *evidence indicates that investors may be able to enhance momentum strategies by exploiting the interactions of valuation (book-to-market ratio) and valuation uncertainty (idiosyncratic volatility) with momentum returns.*

Cautions:

- The investigation is complex in both number of variables considered and variable construction, making implementation of a trading strategy relatively difficult.
- Despite frequent allusions to theory, these complexities invite suspicion of borrowed and created data snooping bias. Such bias represents luck discovered in-sample that would not appear out-of-sample.
- The study reports gross, rather then net returns and alphas. Including reasonable trading frictions would reduce returns and alphas. Moreover, high idiosyncratic volatility likely relates to high trading friction.
- The determination of up and down markets is apparently in-sample (using the entire 1965-2008 data set), such that an investor operating in real time may not determine the same market state.
- Statistical significance tests do not account for potential wildness in stock return distributions.
- The study does not investigate potential weakening of momentum returns over time, and especially after widespread publication of the anomaly.

Originally published at http://www.cxoadvisory.com/12869/value-premium/interactions-of-momentum-value-and-idiosyncratic-volatility/ on March 30, 2011.

Robustness Tests for Ten Popular Stock Return Anomalies

March 28, 2011

In their March 2011 paper entitled "The Shrinking Space for Anomalies", George Jiang and Andrew Zhang investigate the robustness of ten well-known anomalies by iteratively "shrinking the stock space" in two ways to determine whether and how the anomalies really work. The ten anomaly variables are: size, book-to-market ratio, momentum, two liquidity measures, idiosyncratic volatility, accrual, capital expenditure, sales growth and net share issuance. The first way of "shrinking the stock space" involves: (1) ranking the universe of stocks by each of the ten anomaly variables into deciles; (2) iteratively trimming deciles from side of a variable distribution that a hedge portfolio would sell and the side that a hedge portfolio would buy; and, (3) retesting the strength of the anomaly associated with the variable after each iterative trimming. The second way of "shrinking the stock space" involves: (1) trimming from the sample stocks with the smallest market capitalizations and the most extreme book-to-market ratios until size, book-to-market and momentum no longer have significant four-factor alphas for value-weighting and equal equal-weighting (thereby "perfecting" the sample for the four-factor model); and, (2) retesting the strength of the anomalies associated with the other seven variables using the perfected sample. This approach obviates weaknesses in alpha measurement via the commonly applied but imperfect three-factor (market, size, book-to-market) and four-factor (plus momentum) risk models. Using firm characteristics and trading data for all non-financial NYSE, AMEX, and NASDAQ common stocks over the period July 1962 through December 2007, *they find that:*

- Hedge portfolios for the ten anomalies are long (short) stocks with extremely:
  - Small (large) size, measured as market capitalization.
  - Low (high) book-to-market ratios.
  - High (low) return momentum, typically measured over the past year with a skip-month.
  - Low (high) liquidity, typically measured as impact of trading or trading turnover.
  - Low (high) idiosyncratic volatility.
  - Low (high) accruals.
  - Low (high) capital expenditures, measured as asset growth.
  - High (low) sales growth.
  - Low (high) net stock issuance, measured as secondary offerings minus buybacks.
- Regarding the importance of the portfolio weighting scheme used to exploit anomalies:
  - Size, accruals and net stock issuance anomalies are statistically significant for both value and equal portfolio weightings.
  - Momentum and idiosyncratic volatility anomalies are significant only for value portfolio weighting.
  - Book-to-market ratio, liquidity, capital expenditure and sales growth anomalies are

significant only for equal portfolio weighting.

- Regarding the importance of the long (undervalued) and short (overvalued) sides of anomaly variable distributions:
  - Both long and short sides drive the book-to-market ratio and momentum anomalies.
  - The long side drives the size and illiquidity anomalies.
  - The short side drives the accrual, capital expenditure and sales growth anomalies.
- Regarding shortcomings of the four-factor risk adjustment model:
  - Excluding the 6% stocks with the smallest market capitalizations “perfects” the four-factor model for value weighting, in that alphas for the value-weighted size, book-to-market ratio momentum hedge portfolios are no longer highly significant. After this exclusion, only the accrual, net stock issuance and idiosyncratic volatility anomalies remain robust.
  - Excluding first the 8% stocks with the smallest market capitalizations, the 28% of stocks with the lowest book-to-market ratios and the 28% of stocks with the highest book-to-market ratios “perfects” the four-factor model for equal weighting, in that alphas for the equal-weighted size, book-to-market ratio momentum hedge portfolios are no longer highly significant. After these exclusions, only the accrual and net stock issuance anomalies remain robust.
  - In other words (especially for equally weighted portfolios), the four-factor model reliably explains returns only for a subset of the U.S. stock universe. Within this subset, the sales growth and capital expenditures anomalies do not occur, suggesting that they are not independent of the size, book-to-market ratio and momentum anomalies.

In summary, *evidence indicates that successful exploitation of ten widely recognized stock return anomalies may depend on: (1) whether the selected strategy employs equal or value portfolio weighting; (2) whether the selected strategy focuses on overvalued or undervalued stocks per the anomaly definition, or incorporates both; and, (3) whether the strategy excludes parts of the available stock universe (such as the smallest stocks).*

Cautions regarding these findings include:

- The study uses gross, rather than net, returns. Including trading frictions for anomaly implementations could affect conclusions. Momentum (high portfolio turnover) and liquidity (focused on stocks that are expensive to trade) anomalies may be most affected.
- Testing of multiple anomalies on a single data set introduces data snooping bias, such that returns for the best ones incorporate luck. Collecting “documented” anomalies arguably concentrates this bias.

Originally published at http://www.cxoadvisory.com/12818/big-ideas/robustness-tests-for-ten-popular-stock-return-anomalies/ on March 28, 2011.

Bottom-up Anomalies vs. Top-down Portfolio Efficiency

March 21, 2011

How do widely recognized stock return anomalies (return variations unexplained by asset pricing models) mesh with efficient portfolio selection theory? In their paper entitled "Investing in Stock Market Anomalies", Turan Bali, Stephen Brown and Ozgur Demirtas examine five prominent stock market anomalies whose existence is robust through time and across markets (size, book-to-market, short-term reversal, intermediate-term momentum and long-term reversion) in contexts of efficient portfolio selection via mean-variance and stochastic dominance methods. In other words, they test whether portfolios that apply these anomalies exhibit exceptionally good combinations of return and volatility, or obviously outperform on a purely statistical basis. Both these portfolio selection methods have shortcomings related to their inclusion of extreme, impractical choices. The authors consider relaxed ("Almost") versions of these methods that prohibit such choices as "pathological." The authors form value-weighted size and book-to-market portfolios annually and value-weighted reversal, momentum and reversion portfolios monthly. Using monthly data for July 1926 through December 2008 (990 months) for a broad sample of U.S. stocks to construct diversified anomaly portfolios, *they find that:*

- Based on the traditional mean-variance efficient portfolio selection method, only momentum (ranking stocks on 12-month past return, with a skip month) clearly enhances efficiency. Over the entire sample period, momentum winners have both higher average gross return and lower volatility than momentum losers.
- Based on the traditional stochastic dominance portfolio selection method, none of the five anomalies clearly enhance efficiency.
- With relaxed mean-variance and stochastic dominance efficient portfolio selection methods:
  - Small and high book-to-market stocks do not clearly beat big and low book-to-market stocks.
  - Short-term (one-month) losers clearly beat short-term winners.
  - Momentum winners clearly beat momentum losers at a six-month investment horizon.
  - Long-term (return from five years ago to one year ago) losers beat long term winners at investment horizons of one year and longer.
  - An equal-weighted portfolio that combines the high-return parts of all five anomalies clearly beats one that combines the low-return parts at investment horizons of six months to five years.
  - A portfolio that weights equally each of the high-return parts of all five anomalies clearly beats the broad value-weighted U.S. stock market at investment horizons of one to five years.

  - Head-to-head comparisons of pairs of the five anomalies provide some evidence for the superior performance of: (1) size, short-term reversal and momentum for investment horizons of one to 12 months; and, (2) book-to-market and long-term reversion for investment horizons of three to five years.
- The relative strengths of small, high book-to-market, short-term loser, momentum winner and long-term loser stocks increase when investors include consideration of economic variables (monthly inflation rate, monthly growth in industrial production, default spread, aggregate dividend yield and detrended short-term interest rate).

In summary, *evidence from a range of tests employing full distributions of returns provides varying degrees of justification for use of five widely accepted stock return anomalies in the context of formal methods for constructing efficient portfolios. Short-term reversal and intermediate-term momentum appear to be the most valuable anomalies at a gross level.*

Cautions regarding these findings include:

- The study apparently ignores trading frictions in assessing portfolio performance. Realistic trading frictions, especially for portfolios reformed monthly, may well alter return distributions to the point of changing conclusions. In other words, gross and net return distributions may be materially different.
- The study does not investigate whether the anomalies weaken over time.
- The mean-variance efficient portfolio selection method essentially assumes a normal distribution of stock returns, contrary to empirical evidence.
- Ignoring the extreme portfolio choices available via traditional mean-variance and stochastic dominance methods seems similar to exclusion of outliers (wild tail effects) in empirical data. It is not obvious whether the exclusions are merited or simply convenient. People sometimes make “pathological” choices.

Originally published at http://www.cxoadvisory.com/12705/size-effect/bottom-up-anomalies-and-top-down-portfolio-efficiency/ on March 21, 2011.

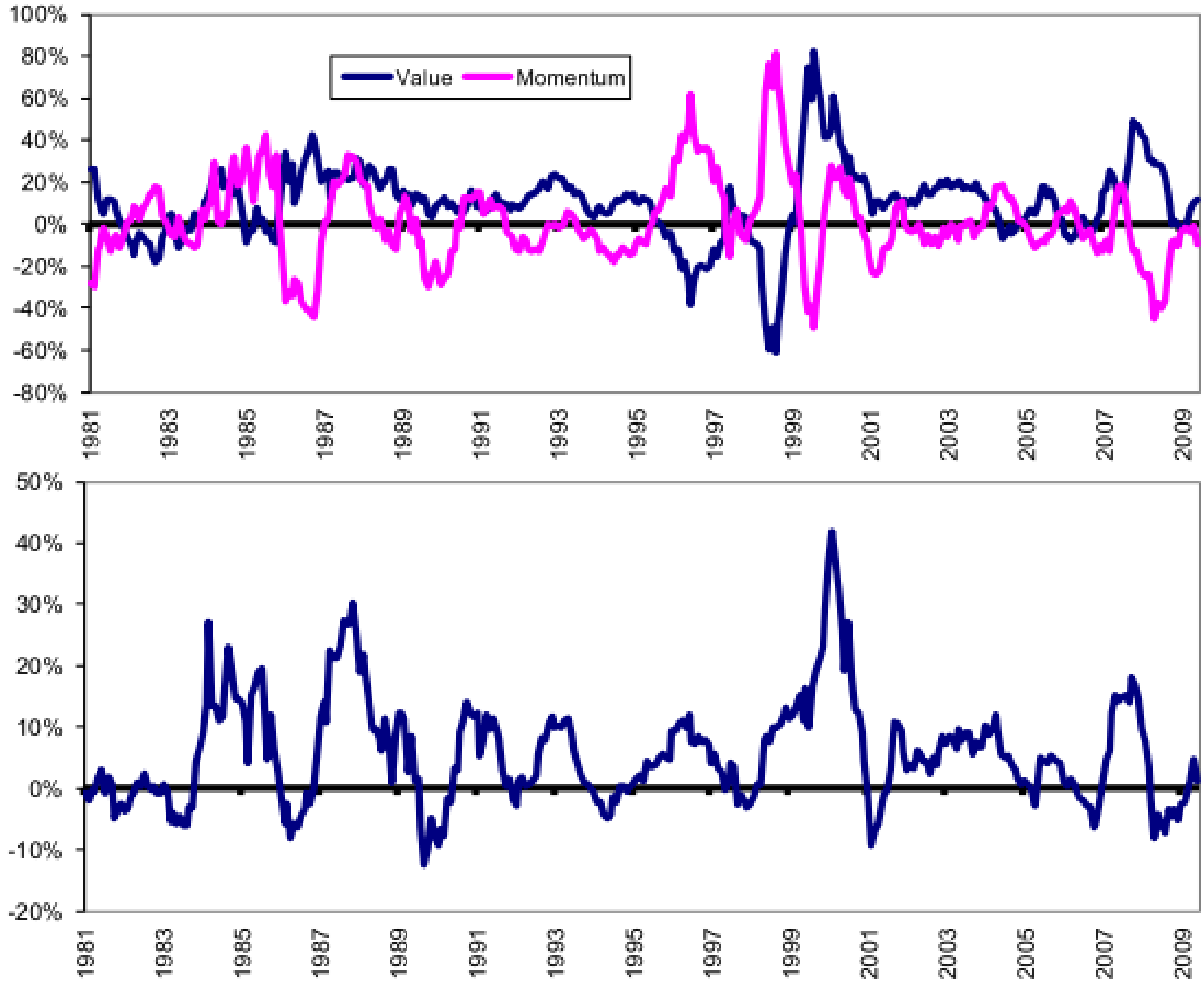
Exclude Japan from Momentum Portfolios?

March 16, 2011

Does momentum not work for Japanese equities? In his March 2011 paper entitled "Momentum in Japan: The Exception that Proves the Rule", Clifford Asness examines whether the failure of stock price momentum in Japan materially undermines belief in momentum investing. He argues that any such examination should adopt the context of value and momentum as an integrated system. His methodology is to rank stocks representing the top 90% of capitalization within each of the U.S., UK, Europe (excluding UK) and Japan into three equal groups by value (book-to-market ratio, with book value lagged six months) or momentum (12-month past return, skipping the most recent month). The spreads in value-weighted returns between the top and bottom thirds define the value and momentum premiums within each geographic market. Using monthly returns for the selected stocks over the period July 1981 through December 2010 (29.5 years), *he finds that:*

- The value and momentum premiums are substantial everywhere over the entire sample period, except for momentum in Japan.
  - Sharpe ratios associated with the value premium are 0.14 for the U.S., 0.38 for the UK, 0.35 for Europe, 0.71 for Japan and 0.57 for the markets combined. Results are statistically significant, except for the U.S. (Europe is borderline).
  - Sharpe ratios associated with the momentum premium are 0.22 for the U.S., 0.48 for the UK, 0.48 for Europe, 0.03 for Japan and 0.38 for the markets combined. Momentum in Japan is effectively zero.
  - A portfolio that invests 50% in each market's value long/short strategy and 50% in that market's momentum long/short strategy, rebalanced monthly, generates a Sharpe ratio of 0.40 for the U.S., 0.84 for the UK, 0.82 for Europe, 0.65 for Japan and 1.01 for the markets combined. These consistently significant results derive from the negative correlations between value and momentum returns over the sample period: -0.59 for the U.S., -0.47 for the UK, -.050 for Europe, -0.55 for Japan and -0.63 for the markets combined.
- Reasons to conclude that the weakness of momentum in Japan does not represent a failure of momentum overall are:
  - The result is consistent with a randomly unfavorable observation within generally pervasive value and momentum effects.
  - An integrated value-momentum system is successful in Japan.
  - A momentum strategy in Japan has a positive three-factor (market, size, book-to-market) alpha because of the negative relationship between value and momentum returns.
  - A Japanese market value-momentum strategy optimizer with perfect foresight would still have given momentum a 30% weight for the sample period.

The following charts, taken from the paper, show rolling 12-month returns for the above-specified Japanese value and momentum strategies separately (upper chart) and integrated as a 50%/50% mix with monthly rebalancing (lower chart). The negative correlation between value and momentum returns is evident in the upper chart. Because of this negative relationship, the integrated strategy generates mostly positive outcomes, and the worst case 12-month return for this portfolio is a relatively benign -13%.



In summary, *despite weak results in Japan, global evidence for stock return momentum investing is strong, especially when viewed as an integrated system with value investing.*

Cautions regarding these findings include:

- The premiums and outcomes described apparently include no trading frictions, which are likely material due to monthly rebalancing of portfolios. Additional rebalancing for integrated value-momentum portfolios likely exacerbates trading frictions.
- Momentum-only investors may want to exclude Japan from their opportunity set as a precaution.

Originally published at http://www.cxoadvisory.com/12619/momentum-investing/exclude-japan-from-momentum-portfolios/ on March 16, 2011.

Concentrating the Value Premium and Momentum with FSCORE

February 11, 2011

Can financial statement analysis expose stocks that investors incorrectly view as value or growth (glamor)? In their February 2011 paper entitled "Identifying Expectation Errors in Value/Glamour Strategies: A Fundamental Analysis Approach", Joseph Piotroski and Eric So investigate stock misvaluation by contrasting firm performance expectations implied by value/growth classification with a simple financial statement metric that differentiates improving versus deteriorating financial performance. This metric (FSCORE, scale 0 to 9), based on nine binary financial statement parameters, measures both the overall financial condition of a firm and the degree to which the firm has improved this condition over the prior year. The authors examine how FSCORE interacts with five widely used relative valuation metrics (book-to-market ratio, cash flow-to-price ratio, earnings-to-price ratio, sales growth and equity share turnover) and with momentum. Using annual financial data and stock returns for a broad sample of firms over the period 1972 through 2008 (117,412 firm-year observations), *they find that:*

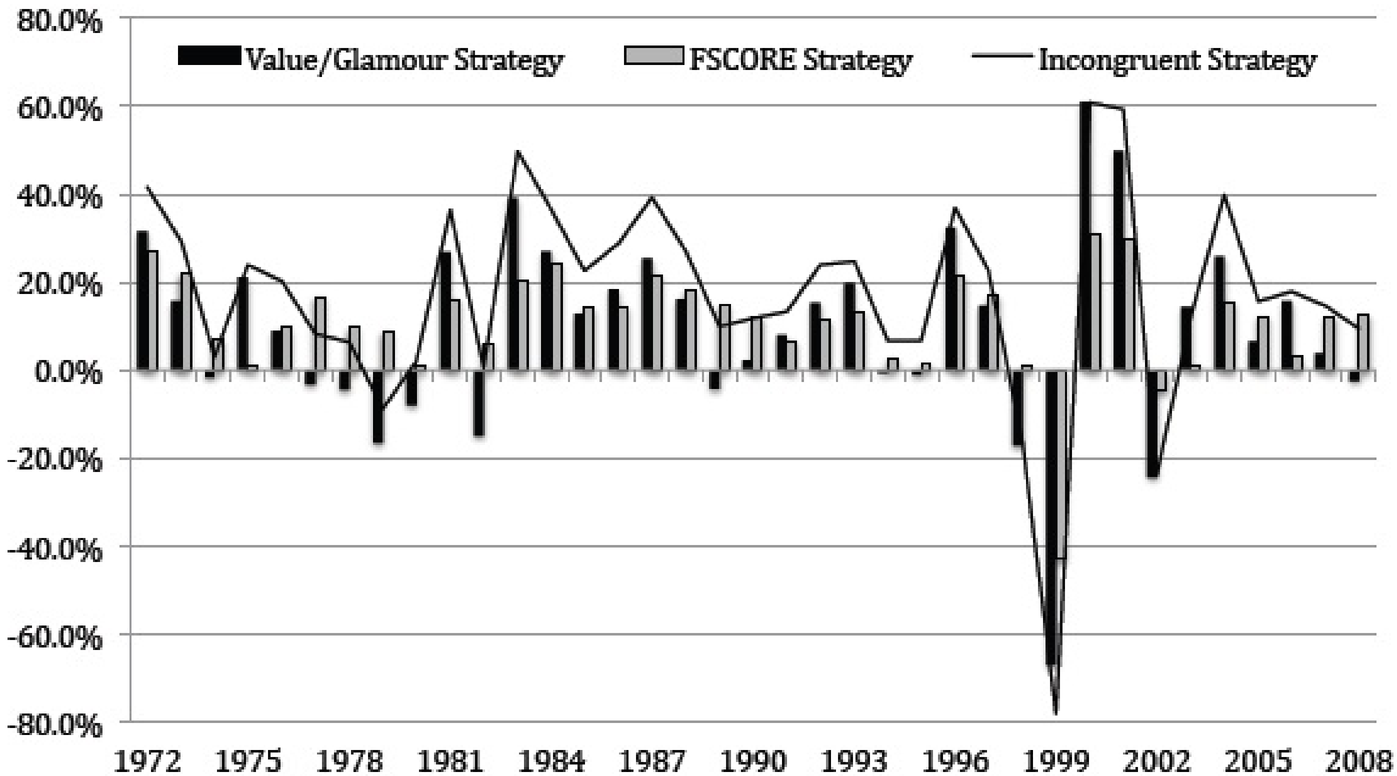
- FSCORE relates positively to book-to-market, earnings-to-price and cash flow-to-price ratios and negatively to sales growth and equity turnover.
- Firms with high FSCOREs tend to realize significantly higher gross future stock returns than those with low FSCOREs, consistent with investor underreaction to changing firm financial condition. For example, firms with FSCORE ≥ 7 (≤ 3) generate an average next-year gross return of 19.1% (6.6%), or 5.5% (-4.3%) on a size-adjusted basis.
- The value premium concentrates in firms whose financial data conflicts with expectations based on a value/growth label, as though investors indiscriminately bundle value and growth stocks and ignore differences within bundles. Among (value) growth stocks, FSCORE most successfully identifies future winners (losers), consistent with FSCORE identifying overly pessimistic (optimistic) expectations.
- Corroborating its effectiveness as a predictor of abnormal returns, FSCORE is a leading indicator of future analyst forecast errors, forecast revisions and returns around earnings announcements.
- A positive (negative) relationship between past and future returns is evident only when upward (downward) six-month momentum coincides with improving (deteriorating) financial performance. For example, the average gross six-month future return for high-momentum/high-FSCORE (high-momentum/low-FSCORE) stocks is 12.4% (1.2%).

The following chart, taken from the paper, presents size-adjusted annual (July-June) gross returns for three hedge portfolios over the entire 1972-2008 sample period:

1. The Value/Glamor Strategy is long (short) the 30% of stocks with the highest (lowest) value based on a composite of the five traditional valuation metrics identified above.

2. The FSCORE strategy is long (short) stocks with an FSCORE ≥ 7 (≤ 3) for the prior year.
3. The Incongruent Strategy, combining traditional valuation metrics with FSCORE fundamental valuation, is long (short) high-value/high-FSCORE (low-value/low-FSCORE) stocks.

The Incongruent Strategy generally produces highest size-adjusted returns, is positive in 33 of 37 years and beats the Value/Glamor Strategy in 34 of 37 years.



In summary, *evidence indicates that investors may be able to enhance the performance of traditional valuation strategies and momentum strategies by combining them with Piotroski's FSCORE ratings.*

Reasons to be cautious about these findings include:

- Return calculations are gross. While trading is infrequent under the portfolio formation rules used, trading frictions would dent reported performance. It is possible that the stocks making the largest gross profitability contributions to the strategies are the least liquid and therefore the costliest to trade.
- Compilation of FSCOREs for a large number of stocks indicates considerable data collection and analysis costs not addressed in the study.
- Reliable exploitation of the findings requires holding a reasonably diverse portfolio of favored stocks, requiring at least a moderate amount of capital.

Originally published at http://www.cxoadvisory.com/11920/fundamental-valuation/concentrating-the-value-premium-and-momentum-with-fscore/ on February 11, 2011.

Reversal, Momentum, Reversion and 12-month Echo Dependencies on January Returns

February 8, 2011

Are January returns important to the profitability of short-term reversal, intermediate-term momentum, long-term reversion and 12-month echo trading strategies? In her December 2010 paper entitled "Momentum, Seasonality and January", Yaqiong Yao investigates the role of January returns within these previously discovered anomalies. The study's core methodology is to reform equally weighted hedge portfolios each month that are long/short stocks in extreme tenths (deciles) of past returns over various intervals. The one-month reversal strategy is long (short) losers (winners) based on prior month returns. Momentum strategies are long (short) winners (losers) based on past 11-month or 12-month returns, with a skip month before portfolio formation to avoid short-term reversal. The reversion strategy is long (short) losers (winners) based on past four-year returns, with a skip-year before portfolio formation to avoid intermediate-term momentum. The 12-month echo strategy is long (short) winners (losers) based on returns for the same month the prior one, two or three years. Using monthly returns for a broad sample of NYSE/AMEX stocks during 1926 through 2009, *she finds that:*

- Past month winners underperform past month losers by an average 3.99% per month gross, supporting incorporation of a skip-month in momentum strategies.
- The 12-month echo (same month last year) drives the finding in prior research that past months 7-12 contribute more to the momentum effect than past months 2-6. The 12-month echo for January is especially influential. Gross momentum profitability tends to disappear during bear markets. The paper offers finer parsing of gross momentum performance by calendar month.
- There is gross long-term reversion from returns of past months 13-23 months and 25-35 months, but the 12-month echoes of past months 24 and 36 work against reversion.
- Trading on 12-month echo generates average monthly gross returns of 0.88%, 0.47% and 0.58% based on returns for past months 12, 24 and 36, respectively. This effect is stronger in the second half of the sample period than the first, is exceptionally strong for January (due most to outperformance of past winners) and tends to persist through bear markets.
- The relationship between current month return and past monthly returns is in some cases decisively different for January in comparison to February-December (see the table below). For example,
    - January exhibits substantial reversion of returns relative to past months 2-11, while February-December exhibits momentum. In other words, momentum consistently does not exist in January.
    - January exhibits notable reversion for past months 13-23 and 25-35, while February-December does not. In other words, long-term reversion is essentially a January effect over the entire sample period and two equal subperiods.

- A combination strategy that exploits the 12-month echo in January and momentum during February-December (excluding as much of bear markets as identifiable) appears particularly attractive.

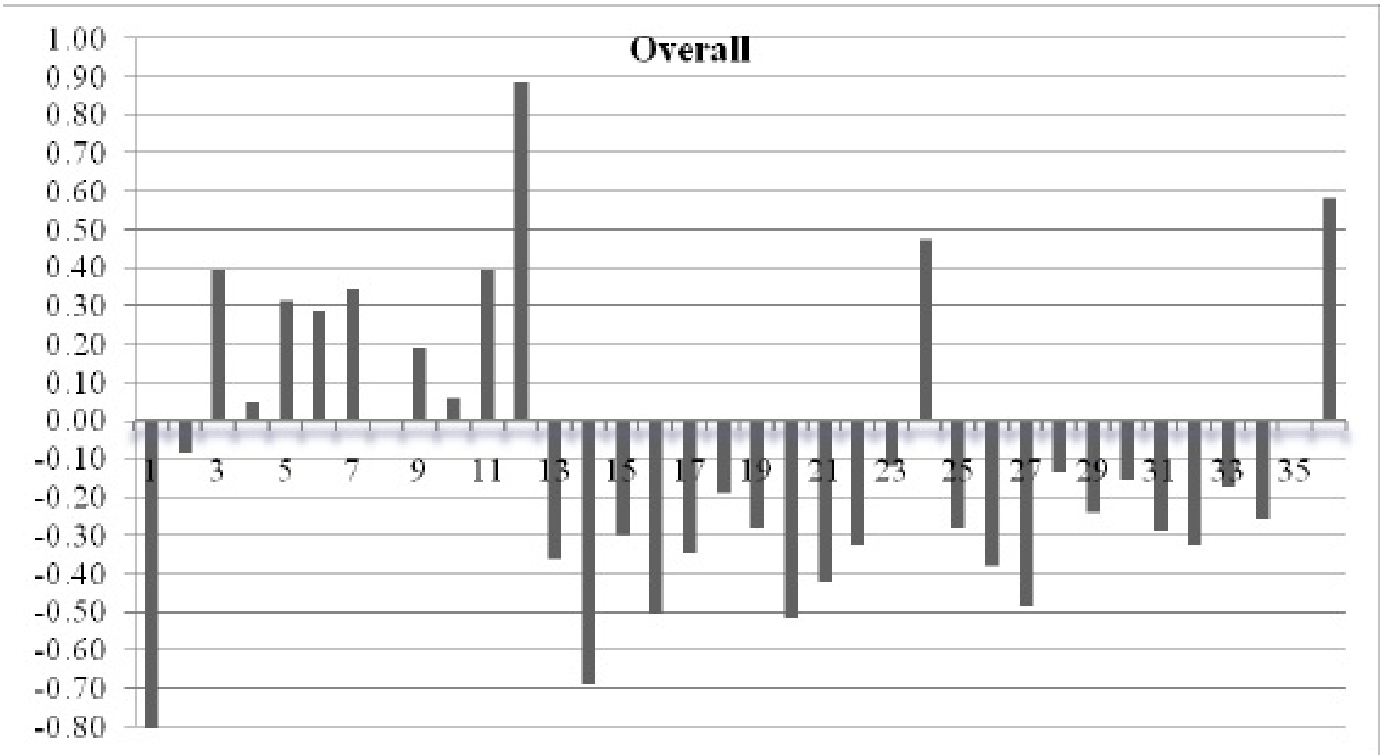
The following table summarizes study findings for all four anomalies over the entire sample period (rows 1-3), the first half of the sample period (rows 4-6) and the second half of the sample period (rows 7-9). Summary findings derive essentially from interpretation of the graphs below for the overall sample period and from similar graphs for the first and second halves of the sample period in the paper.

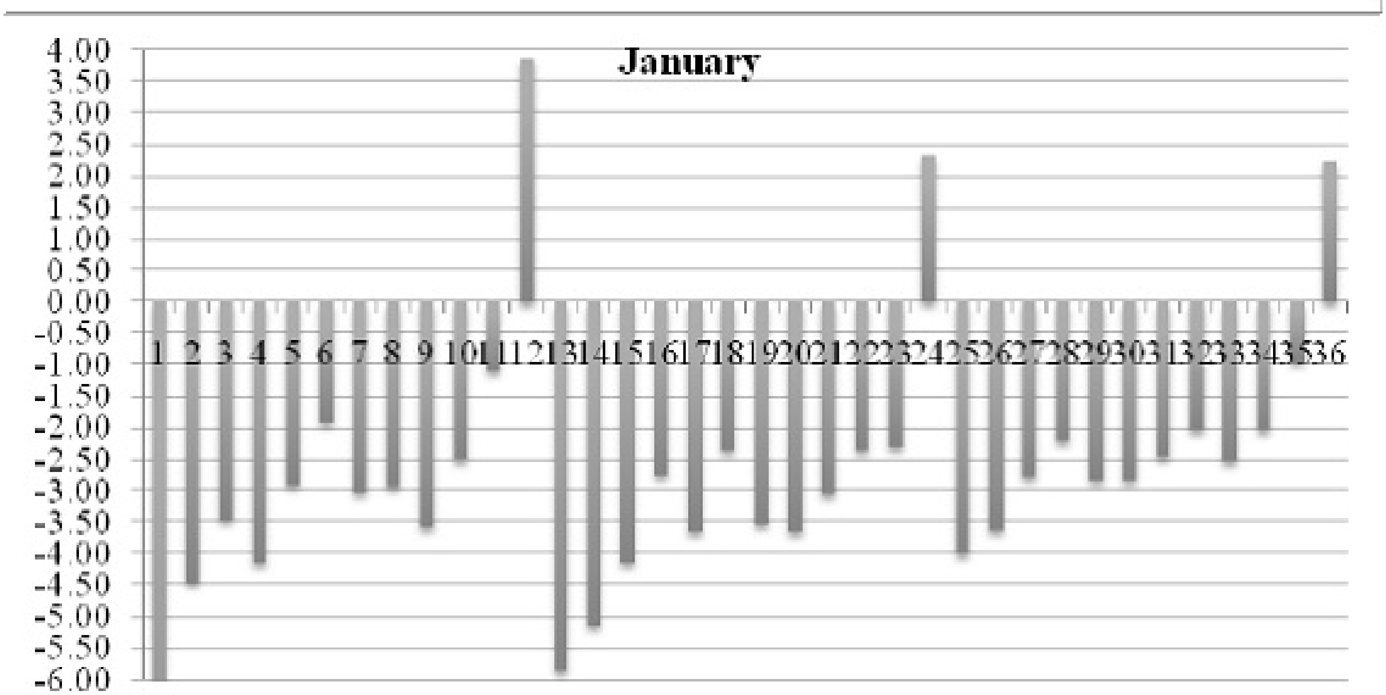
	Short-Term Reversal	Intermediate-Term Momentum	Long-Term Reversion	12-Month Echo
All Months: Entire Sample	Evident and moderately strong	Evident, with 12-month echo important	Evident for past months 13-23 and 25-34, but momentum echoes in past months 24, 36	Evident and moderate to strong for past months 12, 24, 36
January Only: Entire Sample	Evident and very strong	Strong reversals for past months 2-11, but momentum for past month	Evident for past months 13-23 and 25-35, but momentum echoes in past months 24, 36	Evident and moderate to strong for past months 12, 24, 36
February-December: Entire Sample	Evident but modest	Evident and moderate for past months 2-12	Inconsistent for past months 13-23 and 25-35, with momentum echoes in past months 24, 36	Evident and modest to strong for past months 12, 24, 36
All Months: First Half	Evident and moderately strong	Evident, with 12-month echo important	Evident for past months 13-23 and 25-34, but modest momentum echoes in past months 24, 36	Evident and modest to strong for past months 12, 24, 36
January Only: First Half	Evident and very strong	Strong reversals for past months 2-11, but momentum for past month	Evident for past months 13-23 and 25-35, but momentum echoes in past months 24, 36	Evident and strong for past months 12, 24, 36
February-December: First Half	Evident but modest	Evident, with 12-month echo important	Inconsistent for past months 13-23 and 25-35, with hardly any momentum echoes in past months 24, 36	Evident and moderate to modest for past months 12 and 36; not evident for month 24
All Months: Second Half	Evident and moderately strong	Evident, with 12-month echo important	Evident for past months 13-23 and 25-34, but strong momentum echoes in past months 24, 36	Evident and strong for past months 12, 24, 36
January Only: Second Half	Evident and very strong	Strong reversals for past months 2-11, but momentum for past month	Evident for past months 13-23 and 25-35, but momentum echoes in past months 24, 36	Evident and strong for past months 12, 24, 36
February-December: Second Half	Evident but modest	Evident, with 12-month echo important	Not evident for past months 13-23 and 25-35, with moderate momentum echoes in past months 24, 36	Evident and strong for past months 12, 24, 36

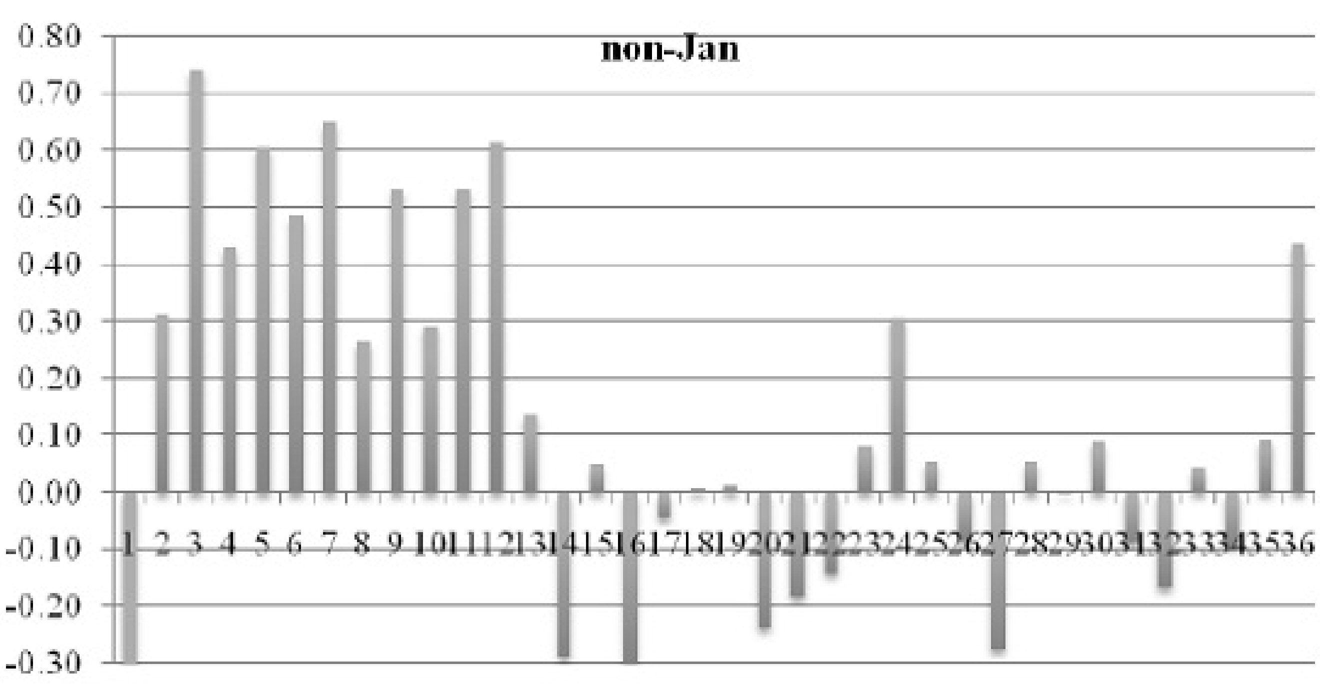
The following charts, taken from the paper, summarize average returns for equally weighted hedge portfolios that are long (short) the tenth of stocks with the highest (lowest) past returns in each of the past 36 months, formed monthly over the entire sample period, as follows:

- The top chart (Overall) shows average returns for portfolios formed in all months across the sample period.
- The middle chart (January) shows average returns only for portfolios formed in January to see whether past return relationships are markedly different for January.
- The bottom chart (non-Jan) shows average returns for portfolios formed in all months except January to confirm whether past return relationships are markedly different for January.

The table above interprets results in the contexts of previously discovered reversal, momentum, reversion and 12-month echo anomalies.







In summary, *investors may be able to refine and combine short-term reversal, intermediate-term momentum, long-term reversion and 12-month echo trading strategies by considering their sometimes unusual behaviors in January compared to the balance of the year.*

Reasons to be cautious about the findings include:

- All study calculations employ gross returns, whereas small and relatively illiquid stocks (with high trading frictions) may drive conclusions. Findings based on realistic net returns may be materially different.
- Finer analysis of time variation than first half/second half may expose market adaptation (material weakening of anomalies after discovery/publication).
- Strategies based on findings may be sensitive to variation in trade execution timing around the turns of months.
- This research carries the unquantifiable baggage of any data snooping bias impounded in the original research on return reversal, momentum, reversion and 12-month echo.
- The detailed parsings of momentum, reversion, 12-month echo, calendar month, subperiod and market conditions explored in the paper carry incremental and potentially material data snooping bias.

Originally published at http://www.cxoadvisory.com/11840/calendar-effects/reversal-momentum-reversion-and-12-month-echo-dependencies-on-january-returns/ on February 8, 2011.

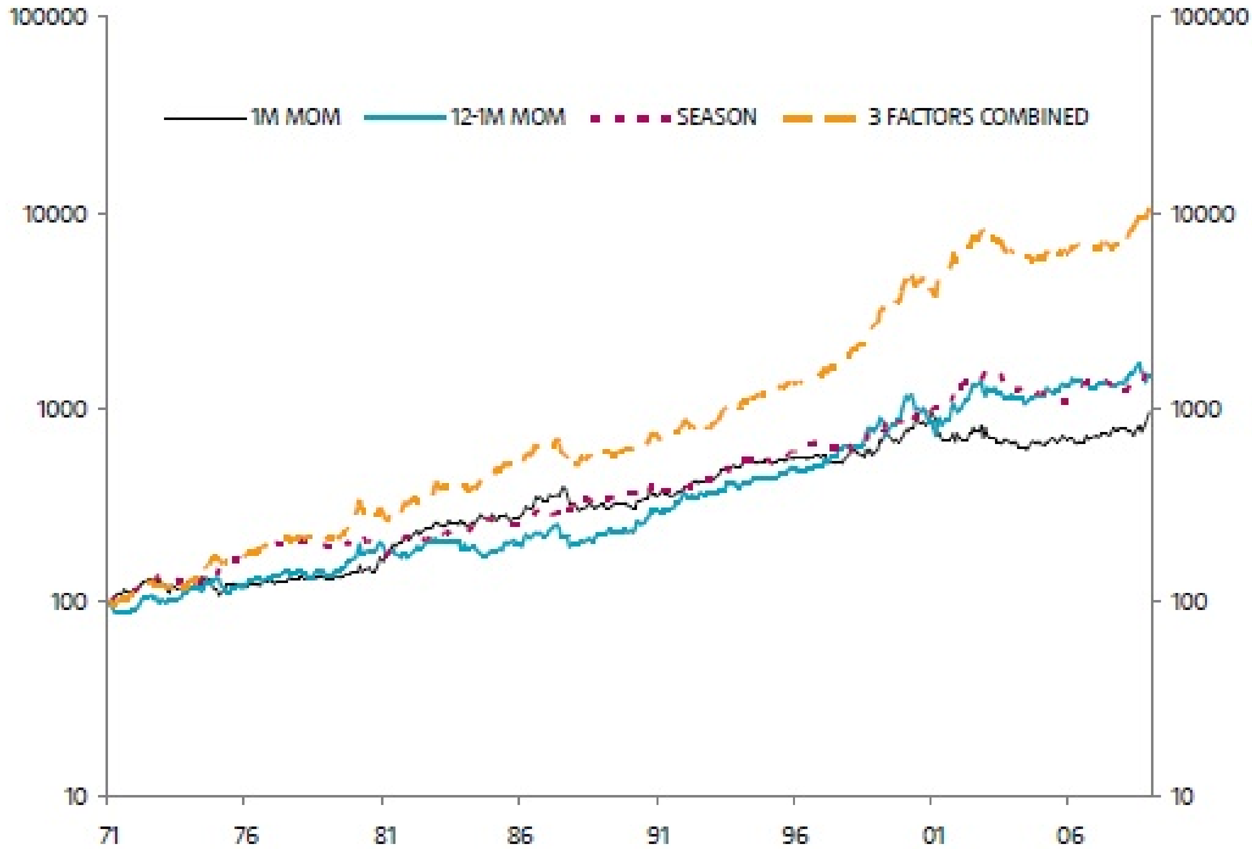
Persistently Effective Sector Selection Variables

January 21, 2011

What variables are persistently effective in picking equity sectors for tactical (monthly) trading? In their July 2010 paper entitled "Global Tactical Sector Allocation: A Quantitative Approach", Ronald Doeswijk and Pim van Vliet investigate the effectiveness of seven variables for tactical trading of ten global equity sector indexes. They test effectiveness of these variables separately and in combination, and after their respective publication dates. The seven variables are: one-month return momentum, 12-1 return momentum (over the 11 months prior to the last month), earnings revision trend, long-term return (over the four years prior to the last year) reversion, aggregate dividend yield, Federal Reserve policy (expansive or contractive) and sell-in-May seasonal. The ten sectors are energy, materials, industrials, consumer discretionary, consumer staples, health care, financials, information technology, telecommunication services and utilities. Testing consists of monthly construction of equally weighted long-short portfolios based on variable conditions. For the first five variables, portfolios are long (short) the top (bottom) three sectors. The Federal Reserve policy and sell-in-May seasonal variables indicate whether to be long or short cyclical versus defensive sectors. The authors calculate net profitability based on a constant 0.60% round-trip trading friction. Using monthly sector index total returns and values for non-return variables mostly over the period 1970 through 2008, *they find that:*

- Average monthly sector index total return ranges from 0.77% (consumer discretionary) to 1.14% (energy). Sector volatility, measured as standard deviation of monthly returns, ranges from 4.0% (consumer staples) to 6.3% (information technology).
- Strategies based on one-month momentum, 12-1 momentum, earnings revision trend and sell-in-May seasonal variables all generate significant abnormal returns over the entire sample period, and some outperformance persists after their respective publication dates.
- Long-term return reversion, aggregate dividend yield and Federal Reserve policy variables are not useful for global sector allocation.
- Average effectiveness of the seven variables in selecting sectors declines by about one third after their respective publication dates.
- Over the entire sample period, a hedge strategy that combines via a simple sector scoring system the two momentum variables and the sell-in-May seasonal variable:
    - Generates an annual compound gross return of 12.9%, 5% higher than the best single-variable strategy (see the chart below), with the associated 507% turnover leaving an annual compound net return of 9.9%.
    - Has a monthly (annual) success rate of 63% (82%).
    - Exhibits about 17% annual return volatility and severe drawdowns.
    - Assuming a one third post-publication decay, translates to an expected annual compound net return of about 5.6%.
- The Fama-French three-factor model (market, size and value) does not explain the abnormal returns of the combination strategy.

The following chart, taken from the paper, compares on a logarithmic scale over the entire 1971-2008 sample period the cumulative performances of individual one-month momentum, 12-month momentum and sell-in-May seasonal global sector allocation strategies, and a strategy that combines these three variables. The combination strategy employs a simple sector scoring system based on monthly quintile rankings for each of the two momentum variables (0, 1, 2, 3 or 4) and monthly seasonal attractiveness ratings (0, 2 or 4) such that maximum sector total score is 12. The combination portfolio is long (short) sectors scoring above 9 (below 3), with each sector position held until its score crosses below (above) 6. Based on these rules, the combination strategy is typically long two or three sectors and short two or three sectors. Results show that the combination strategy substantially outperforms all three individual strategies.



In summary, *investors may be able to earn substantial abnormal returns via a strategy that allocates investments to global equity sectors based on a combination of momentum (short-term and intermediate-term) and seasonal (sell-in-May) indicators.*

Reasons to be cautious about the findings of this study are:

- The study backtests use a static and modern level of trading friction. However, actual trading friction varies considerably during the sample period (see "Trading Frictions Over the Long Run"). Use of the dynamic historical level of trading friction could materially alter findings.
- While the post-publication effectiveness tests mitigate data snooping bias for the variables individually, there may be snooping bias associated with the sector scoring system used in constructing the combination strategy.

- Results may be sensitive to the speed with which an investor reacts to sector trading signals.

See “Simple Sector ETF Momentum Strategy Performance” and related entries for investigation of various momentum strategies as applied to U.S. equity sector exchange-traded funds since the end of 1998.

Originally published at http://www.cxoadvisory.com/11522/calendar-effects/persistently-effective-sector-selection-variables/ on January 21, 2011.

Combination Momentum Strategies Not Worth the Effort?

December 29, 2010

Why does some prior research find that double sorts, first on some non-return variable and then on past returns, enhance momentum strategy performance? Are the enhancements truly distinct from momentum, or do they just pick higher momentum stocks? In their December 2010 paper entitled “One Effect or Many: Sources of Momentum Profits and Pitfalls of Double-Sorting”, Pavel Bandarchuk and Jens Hilscher investigate why sorting stocks first on some firm/stock characteristic and then on past returns elevates momentum profits. Specifically, they examine in several ways the relationship between each of size (market capitalization), return R-squared (similar to idiosyncratic volatility), turnover (12-month average), age (years listed), stock price, illiquidity (average absolute weekly return divided by weekly dollar volume) and credit rating and past returns to investigate the incremental profits of combining each with momentum. They use the logarithm of six-month past return with skip-month (effectively, a five-month return) to measure momentum. They calculate average future returns based on equal weighting and monthly portfolio reformation. Using weekly and monthly data for a broad sample of U.S. stocks spanning 1964 through 2008 (3,187 stocks per month on average), *they find that:*

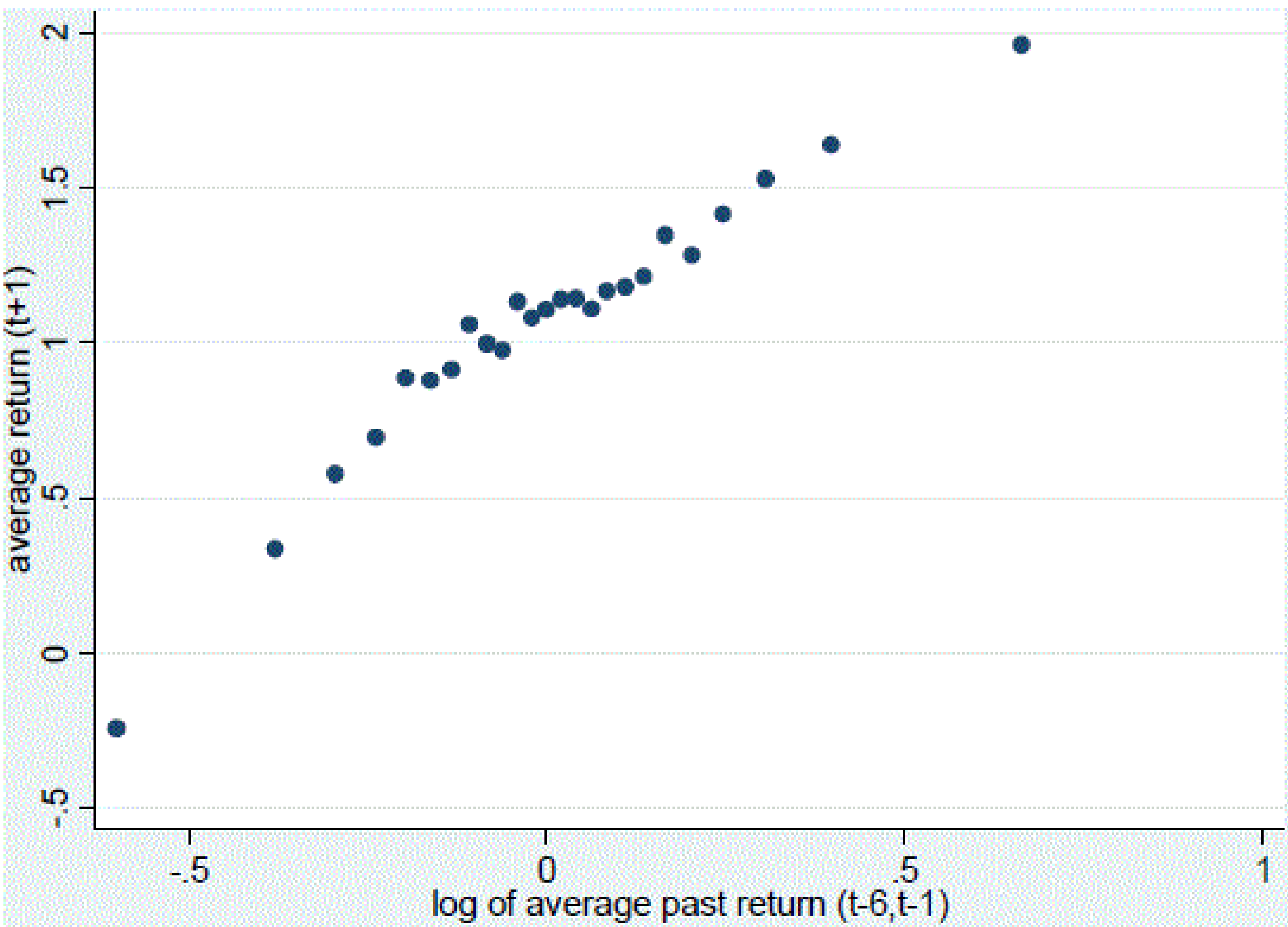
- The relationship between momentum and future returns is positive and systematic (see the chart below). Over the entire sample period, a hedge portfolio that is long (short) the half of stocks with the highest (lowest) past returns generates an average monthly gross return of 0.55%. Selecting the stocks with the highest and lowest 10% (4%) of past returns boosts average monthly gross return to 1.6% (2.2%).
- Sorting on idiosyncratic volatility (measured with weekly data over the past year) rather than past returns produces similar results, because high-volatility stocks are more likely to be high-momentum stocks. The average monthly gross return for the fifth of stocks with the highest (lowest) lagged idiosyncratic volatility is 2.0% (close to zero).
- Stocks with extreme momentum (top and bottom tenths of past returns) have on average 35% lower market capitalization, 15% lower return R-squared, 82% higher turnover, 39% lower time listed, 26% lower price, 96% lower liquidity and lower credit rating than those in the middle of the past return distribution (middle 20%).
- For most of these characteristics, momentum profits increase systematically across sorted fifths. For example, average monthly gross momentum hedge returns (high minus low quintiles) are 0.53%/1.17%/1.34% for the fifths of stocks with the largest /middle/ smallest market capitalizations. This kind of double-sort enhancement is largest (smallest) for credit rating (R-squared).
- Double quintile sorting first on firm/stock characteristics and then on past returns tends to generate portfolios with more extreme past returns. Adjusting for the effect on past returns nearly eliminates the benefit of double sorting. Idiosyncratic volatility appears to be the common connection between characteristics and past returns.

- Specifically, a momentum-only strategy comparable to the the quintile double sorts (long the 4% of stocks with the highest past returns and short the 4% with the lowest) generates an average monthly gross return of 2.2%, beating or matching all double-sort strategies.

The following chart, taken from the paper, plots average monthly gross percentage returns for 25 portfolios sorted on the logarithm of past returns from six months prior through one month prior, equally weighted and reformed monthly over the entire sample period. In general, past winners (high past returns) outperform past losers (low past returns), and this outperformance tendency is highly systematic. In other words, the more extreme the past returns, the higher the average monthly gross profitability of a momentum strategy.

As described above, double sorting first on various firm/stock characteristics and then on past returns essentially just selects stocks with higher past returns.

Note that stocks with extreme past returns may have low liquidity, complicating exploitation of momentum on a net basis.



In summary, *evidence indicates that presorting on other firm/stock characteristics can enhance momentum strategy returns, but such double sorting is no better than a simple momentum strategy based on especially extreme past returns.*

Note that:

- Return calculations in this study are gross, not net.
- The momentum strategies described likely involve high portfolio turnover, such that trading frictions would substantially dent gross profits. Moreover, as noted above, the highest momentum stocks may bear the highest trading frictions. High-turnover strategies are especially problematic for individuals, whose stock-by-stock positions tend to be small.
- Stocks with high momentum also tend to be volatile, such that high average monthly returns may not translate to similarly attractive cumulative returns.

Originally published at http://www.cxoadvisory.com/11009/momentum-investing/combination-momentum-strategies-not-worth-the-effort/ on December 29, 2010.

OTC Stock Returns

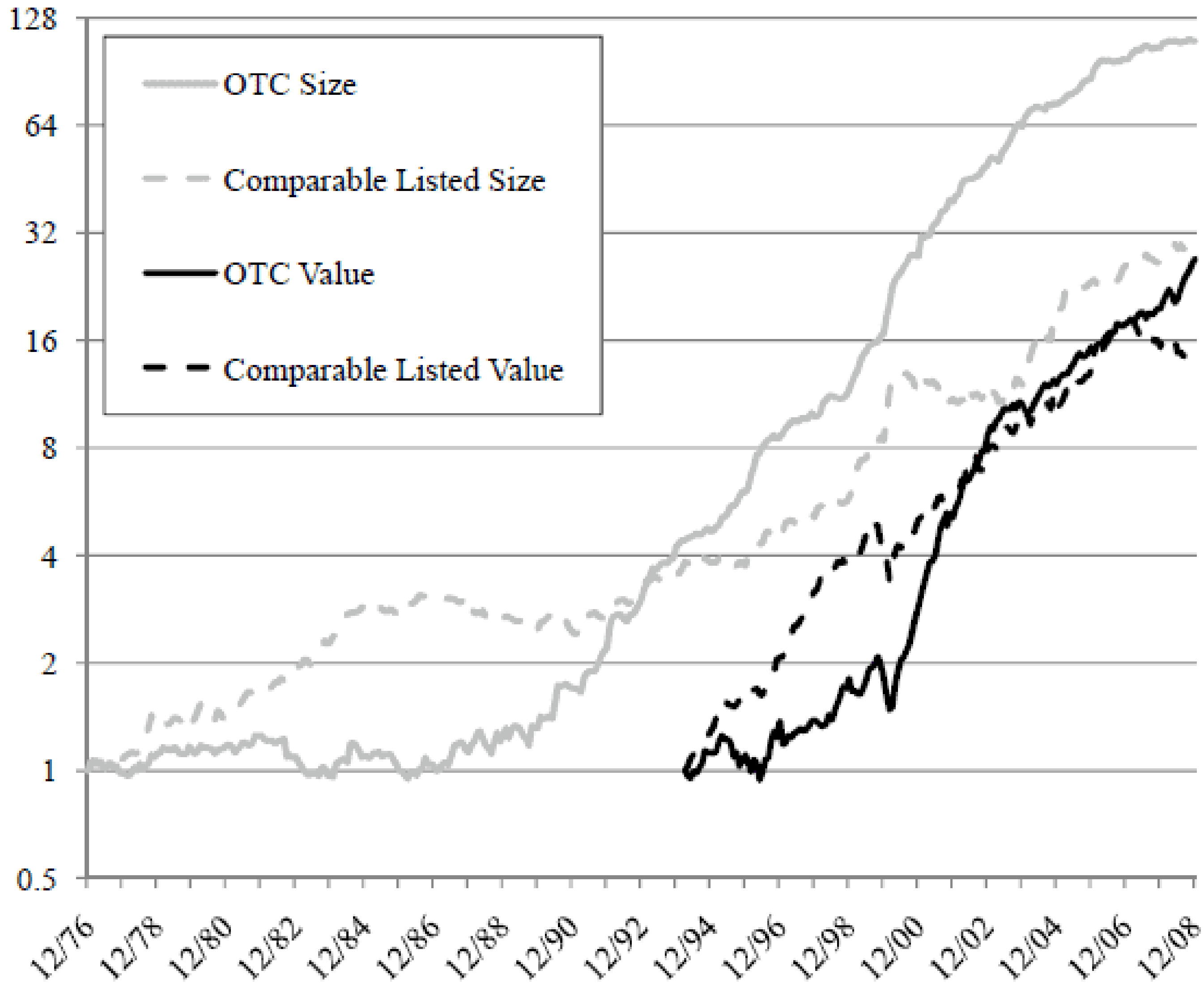
December 6, 2010

Does the relatively illiquid, opaque, retail environment of over-the-counter (OTC) stocks make them behave differently from comparable listed stocks? In their November 2010 paper entitled "The Cross Section of Over-the-Counter Equities", Andrew Ang, Assaf Shtauber and Paul Tetlock test the abilities of market capitalization, book-to-market ratio, liquidity, return momentum and idiosyncratic volatility to predict OTC stock returns and compare results to those for listed stocks with comparable market capitalizations. As a part of the study, they examine hedge portfolios that are long/short extreme fifths of OTC stocks ranked by these characteristics to estimate of the magnitudes of the respective premiums. Using trading volumes, market capitalizations, book-to-market ratios (as available) and closing, bid and ask prices for a large sample of OTC-only firms with at least one Financial Industry Regulatory Authority market maker, and for comparable listed firms, during 1975 through 2008, *they find that:*

- Over the entire sample period, the gross average monthly return of OTC (comparably sized listed) stocks is -0.26% (0.69%).
- The average standard deviation of monthly returns for OTC (comparably sized listed) stocks is 6.80% (5.25%). The standard deviation of monthly returns across sampled OTC (comparably sized listed) stocks is 27.8% (19.3%).
- OTC stocks have a somewhat lower average book-to-market ratio, a much lower average trading volume and a markedly higher average bid-ask spread than comparably sized listed stocks.
- In general, regressions indicate that firm/stock characteristics have far greater predictive power for OTC stocks than for comparably sized listed stocks.
- Regardless of the liquidity measure used, the illiquidity premium is much higher for OTC stocks than for comparably sized listed stocks. For example, the gross annual premium indicated by a portfolio that is long (short) the fifth of stocks with the highest (lowest) fraction of days with zero volume during the preceding month (reformed monthly) is 21.5% for OTC stocks and 1.7% for comparably sized listed stocks.
- The size effect and value premium are similar for OTC stocks and comparably sized listed stocks (see the chart below).
- However, the momentum effect and idiosyncratic volatility premium, while pronounced for comparably sized listed stocks, are small to non-existent for OTC stocks.

The following chart, taken from the paper, compares on a logarithmic scale the gross cumulative values of $1 initial investments from December 1976 through December 2008 in hedge portfolios exploiting the size effect and the value premium for OTC stocks and comparably sized listed stocks. The size portfolios are long (short) the fifth of stocks with the smallest (biggest) prior-month market capitalizations, weighted equally and reformed monthly. The value portfolios are long (short) the fifth of stocks with the highest (lowest) prior-month book-to-market ratios, widely available only after 1993, weighted equally and reformed monthly. As a risk adjustment, the authors scale OTC portfolio positions so that the volatility of the OTC portfolio is equal to that of comparably sized listed portfolio.

Results indicate that the size effect and value premium exist for OTC stocks, with risk-adjusted magnitudes roughly similar to those for comparably sized listed stocks.



In summary, *evidence from multiple tests indicates that OTC stocks present at the gross level a much larger illiquidity premium, a similar size effect, a similar value premium, a much smaller momentum effect and a much smaller idiosyncratic volatility premium relative to comparably sized listed stocks.*

Note that all return calculations in this study are gross. Monthly portfolio reformation implies considerable trading. OTC stocks have relatively large bid-ask spreads, and the impact on price of substantial trading in these stocks is not negligible. Accounting for reasonable trading friction would materially diminish the estimated gross premiums, and plausibly could eliminate or reverse them.

Originally published at http://www.cxoadvisory.com/10706/size-effect/otc-stock-returns/ on December 6, 2010.

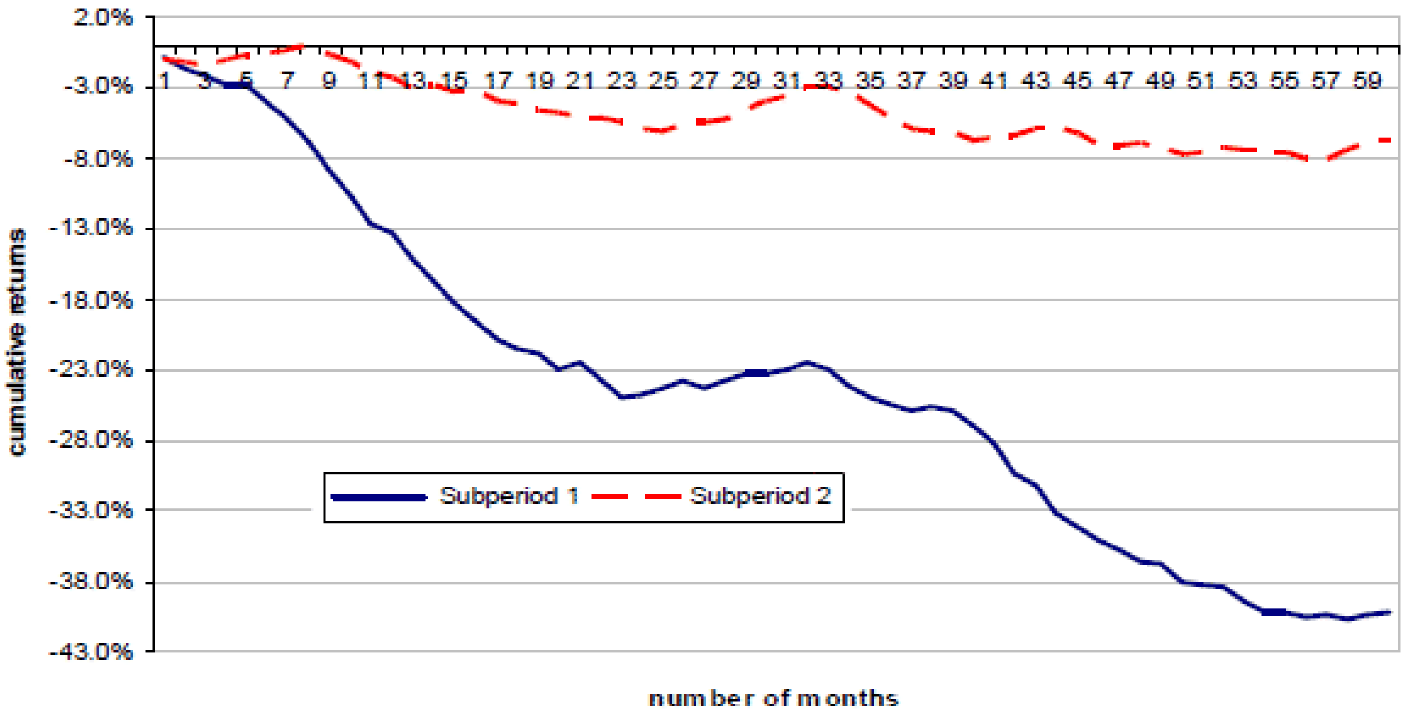
52-Week Highs for Emerging Markets Indexes

December 3, 2010

Evidence indicates that 52-week highs may be effective momentum signals for individual stocks, but probably not for major U.S. indexes. What do 52-week highs indicate for emerging markets? In their paper entitled "Predictability of Future Index Returns Based on the 52-Week High Strategy", Mirela Malin and Graham Bornholt investigate the predictive power of 52-week highs for future returns of emerging markets indexes. To test the power of the 52-week high, they form monthly portfolios that are long (short) the fourth of emerging markets indexes that rank fractionally nearest to (farthest from) their respective 52-week highs and measure returns over the next 1, 3, 6, 9 and 12 months. They also test for comparison similar momentum portfolios with ranking intervals of 3, 6, 9 and 12 months and the same holding intervals. Both strategies insert a skip-month between ranking and portfolio formation. Using monthly dividend-adjusted levels and 52-week highs for 26 emerging markets indexes as available during January 1988 through March 2009 (171 to 255 months per index), *they find that:*

- The 52-week high strategy is unprofitable for all holding periods. For a 6-month holding period, it generates a monthly gross loss of 0.27%.
- In contrast, a 6-month holding period for the momentum strategy generates a monthly gross profit 0.84%.
- The problem with the 52-week high strategy for emerging markets, unlike developed markets, is that its short positions earn large future returns (annual alpha exceeding 14%). Filtering the short side of the portfolio to exclude indexes with high recent volatility eliminates its abnormally high future returns, but this modified 52-week high strategy is less profitable than a comparable momentum strategy.

The following chart, taken from the paper, presents the average cumulative gross returns of the 52-week high strategy with 1-month holding period for emerging markets indexes over rolling 60-month intervals for two subperiods: January 1988 through December 1998 (Subperiod 1), and January 1999 – March 2009 (Subperiod 2). Both graphs indicate the strategy is unprofitable, with the difference in performance indicative of modest statistical reliability.



In summary, *evidence indicates that 52-week highs do not predict strong future returns for emerging market indexes.*

Note that the study is conceptual only in that it:

- Uses indexes rather than tradable index proxies (such as exchange-traded funds), thereby ignoring proxy formation/maintenance fees and frictions.
- Ignores index switching frictions.

Originally published at http://www.cxoadvisory.com/10583/technical-trading/52-week-highs-for-emerging-markets-indexes/ on December 3, 2010.

Stock Index Returns after 52-week Highs and Lows

November 8, 2010

Do stock indexes react systematically to extreme price levels, such as 52-week highs and 52-week lows? To investigate, we consider the behaviors of the Dow Jones Industrial Average (DJIA), the S&P 500 Index and the NASDAQ Composite Index over the 13 weeks after 52-week highs and lows during their available histories. Using weekly levels of these indexes from October 1928, January 1950 and February 1971, respectively, through October 2010, *we find that:*

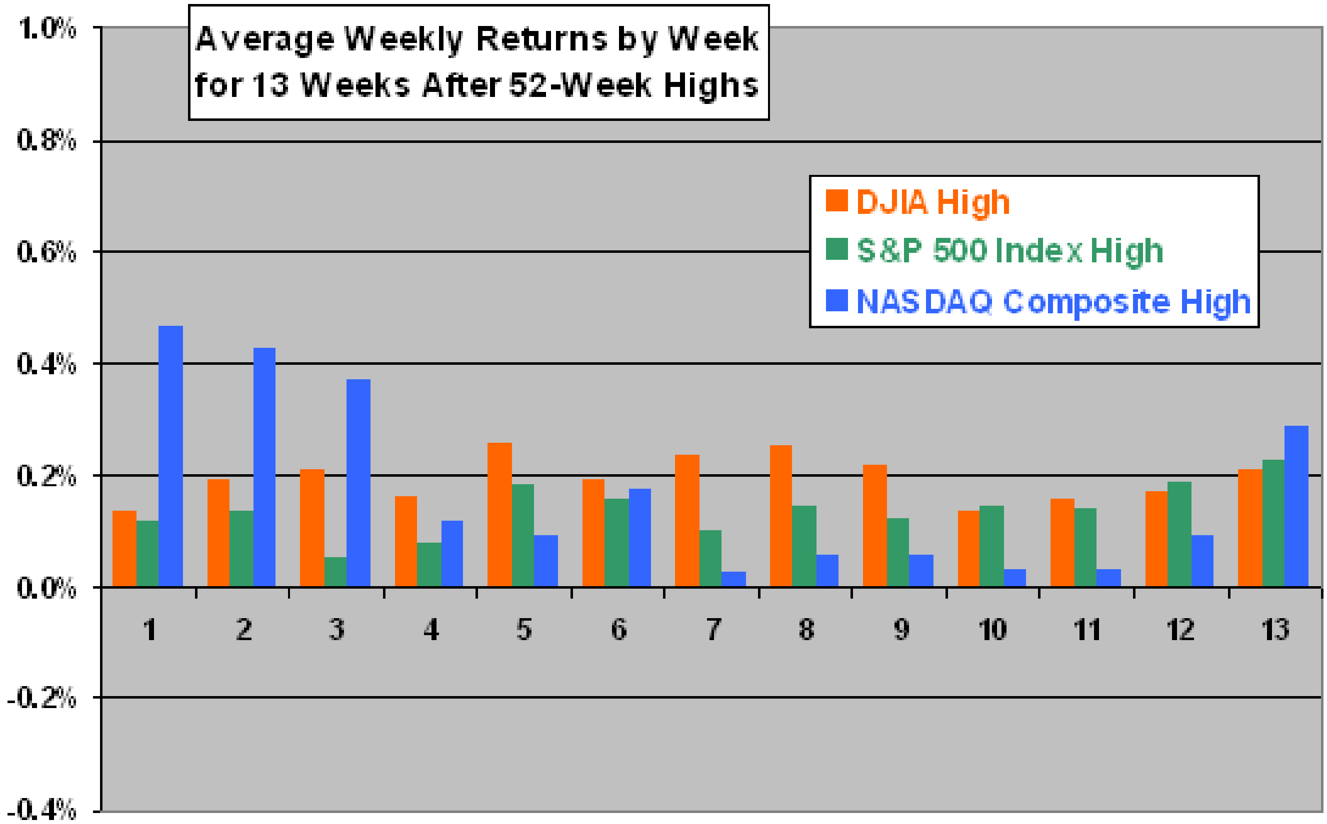
Over the respective available sample periods:

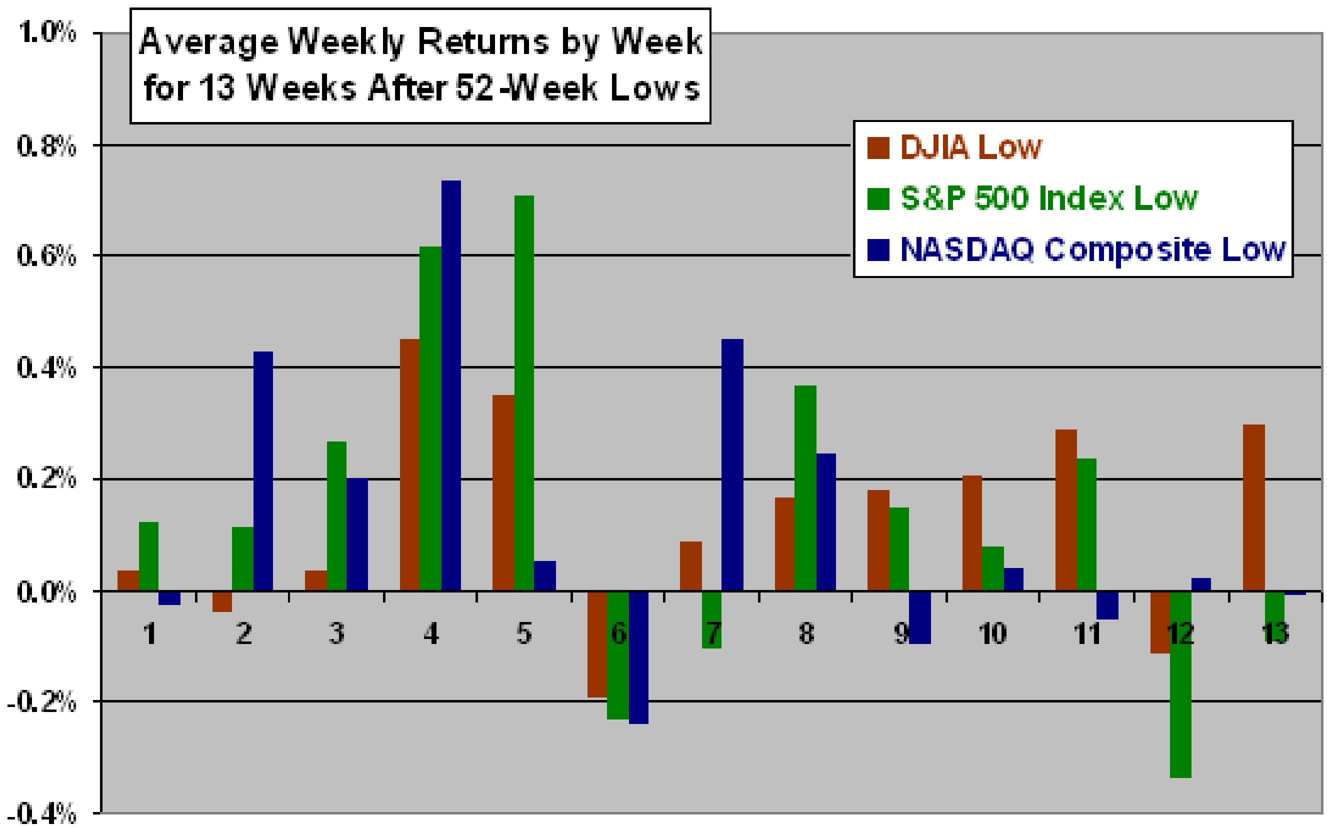
- DJIA has 685 52-week highs and 191 52-week lows (ratio 3.6:1).
- The S&P 500 Index has 568 52-week highs and 129 52-week lows (ratio 4.4:1).
- The NASDAQ Composite Index has 368 52-week highs and 105 52-week lows (ratio 3.5:1).

The following two charts summarize average returns by week for 13 weeks after 52-week highs (upper chart) and 52-week lows (lower chart) over the available sample periods. The average weekly returns for DJIA, the S&P 500 Index and the NASDAQ Composite Index over these sample periods are 0.12%, 0.16% and 0.20%, respectively. Results indicate that weekly returns during the quarter after 52-week highs (lows) tend to be positive and placid (volatile with an initial reversal).

The consistency of the reversal for two to five weeks after 52-week lows, and the end of the reversal during the sixth week, is notable.

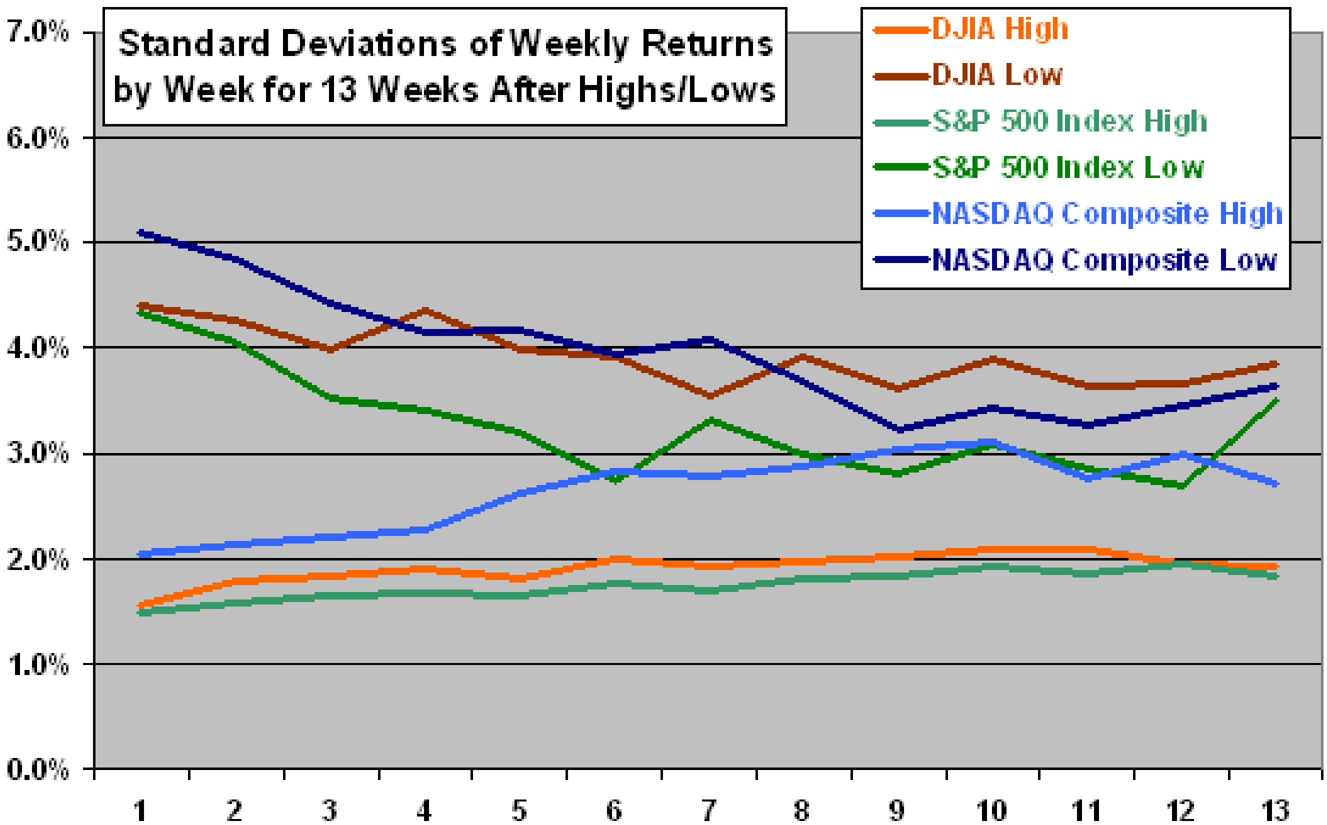
For a different perspective, we look at standard deviations of weekly returns.





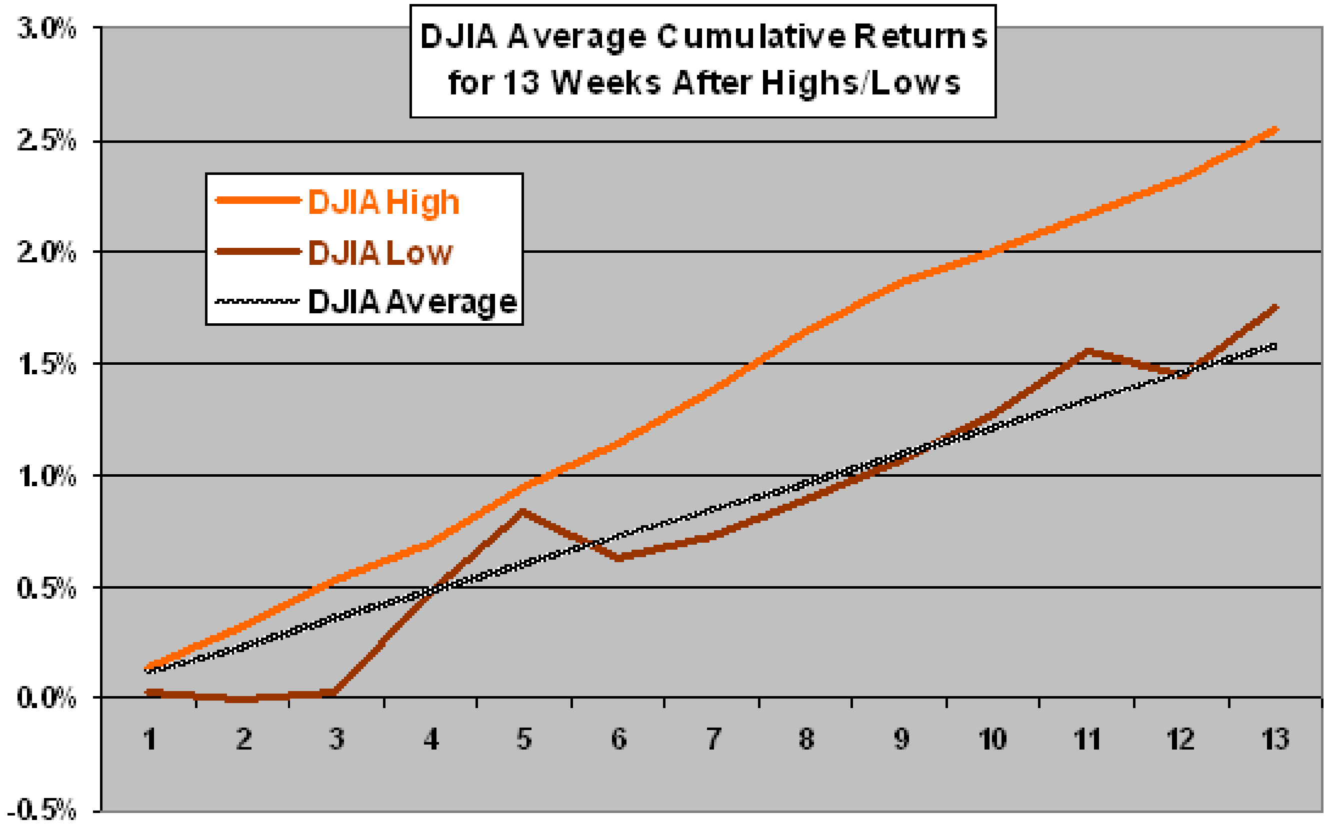
The next chart summarizes standard deviations of weekly returns by week for 13 weeks after 52-week highs and lows over the available sample periods. The standard deviations of all weekly returns for DJIA, the S&P 500 Index and the NASDAQ Composite Index over these sample periods are 2.48%, 2.08% and 2.80%, respectively. Results confirm that indexes tend to be less (more) volatile during the quarter after 52-week highs (lows).

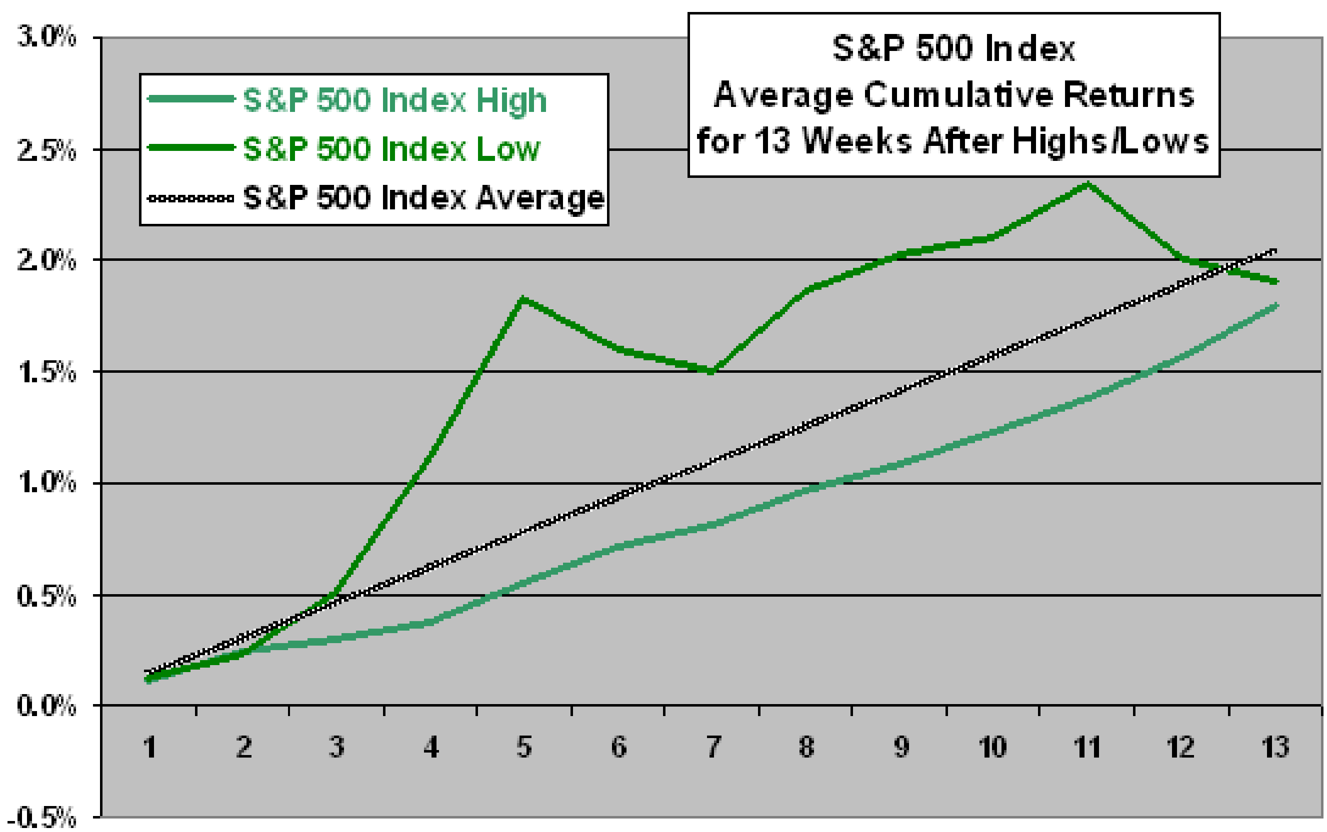
How do the average returns by week translate into cumulative returns?

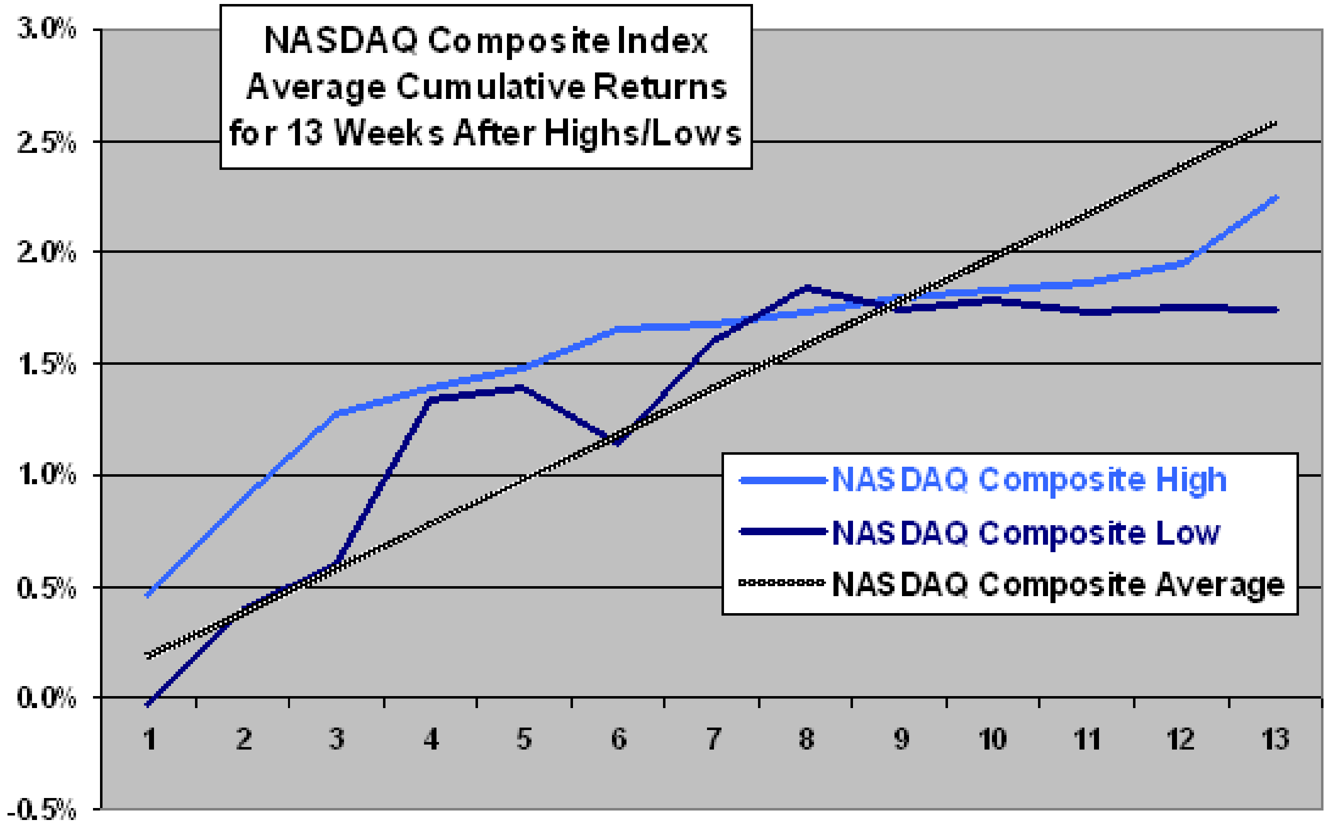


The last three charts summarize average cumulative returns during the 13 weeks after 52-week highs and lows for DJIA (upper chart), the S&P 500 Index (middle chart) and the NASDAQ Composite Index (lower chart) over the available sample periods. For comparison, each chart includes the cumulative return based on average weekly return over the available sample period for the applicable index.

Results are inconsistent across indexes/sample periods, but performances after 52-week highs and lows do not deviate markedly from benchmarks. These inconsistencies undermine belief in a reliable equity market reaction to index 52-week highs and lows.


DJIA Average Cumulative Returns for 13 Weeks After Highs/Lows
DJIA High
DJIA Low
DJIA Average
3.0%
2.5%
2.0%
1.5%
1.0%
0.5%
0.0%
-0.5%
1
2
3
4
5
6
7
8
9
10
11
12
13


S&P 500 Index Average Cumulative Returns for 13 Weeks After Highs/Lows
S&P 500 Index High
S&P 500 Index Low
S&P 500 Index Average
3.0%
2.5%
2.0%
1.5%
1.0%
0.5%
0.0%
-0.5%
1
2
3
4
5
6
7
8
9
10
11
12
13



One reservation about these findings is that highs and lows tend to cluster, making subsequent return measurement intervals overlap. Interval overlap may distort statistics from the perspective of independently tradable events.

In summary, *evidence from simple tests on three indexes indicates that stock market indexes tend to be placid (volatile) during the quarter after 52-week highs (lows), with cumulative performances not markedly different from averages.*

Originally published at http://www.cxoadvisory.com/9957/technical-trading/stock-index-returns-after-52-week-highs-and-lows/ on November 8, 2010.

Highly Simplified Momentum Strategies

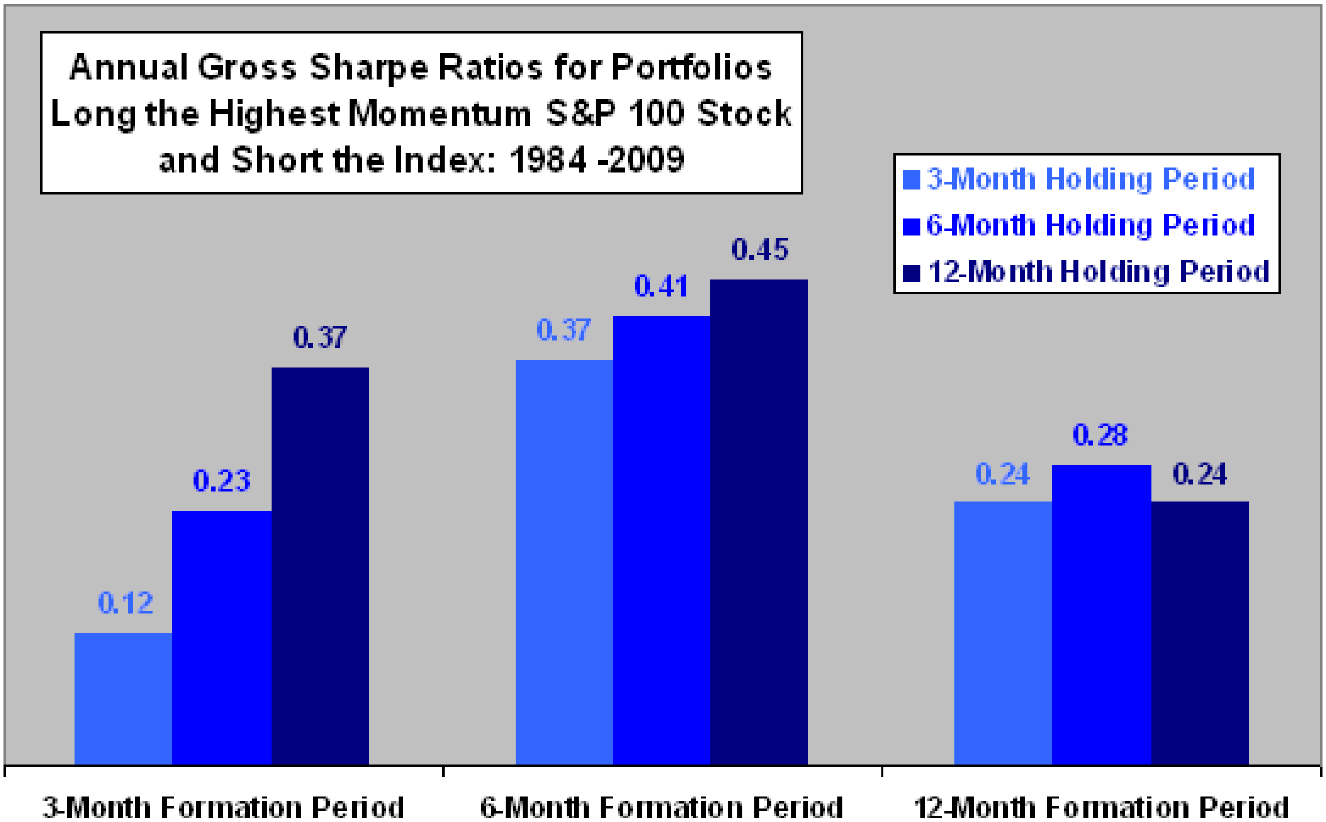
October 26, 2010

Academic tests of momentum generally involve frequent adjustments to portfolios of many stocks, such that trading frictions and shorting/capacity restrictions make implementation impractical for both large and small investors. Are there simplified approaches that successfully shed trading frictions faster than momentum returns? In the October 2010 version of their paper entitled "Feasible Momentum Strategies in the US Stock Market", Manuel Ammann, Marcel Moellenbeck and Markus Schmid measure the returns of simple, low-cost momentum strategies restricted to the relatively liquid U.S. stocks in the S&P 100 Index. They form portfolios monthly for nine combinations of ranking and holding periods (3, 6 and 12 months for both), including a skip-month between ranking and formation to avoid reversals. They consider the best-performing 1, 3, 5 and 10 stocks for long positions and either their worst-performing counterparts or the S&P 100 Index for short positions. They impose an overarching annual rebalancing scheme across different holding periods to suppress return volatility. Using total return data for the stocks in the S&P 100 Index as it exists at time of portfolio formation spanning 1982 through 2009, *they find that:*

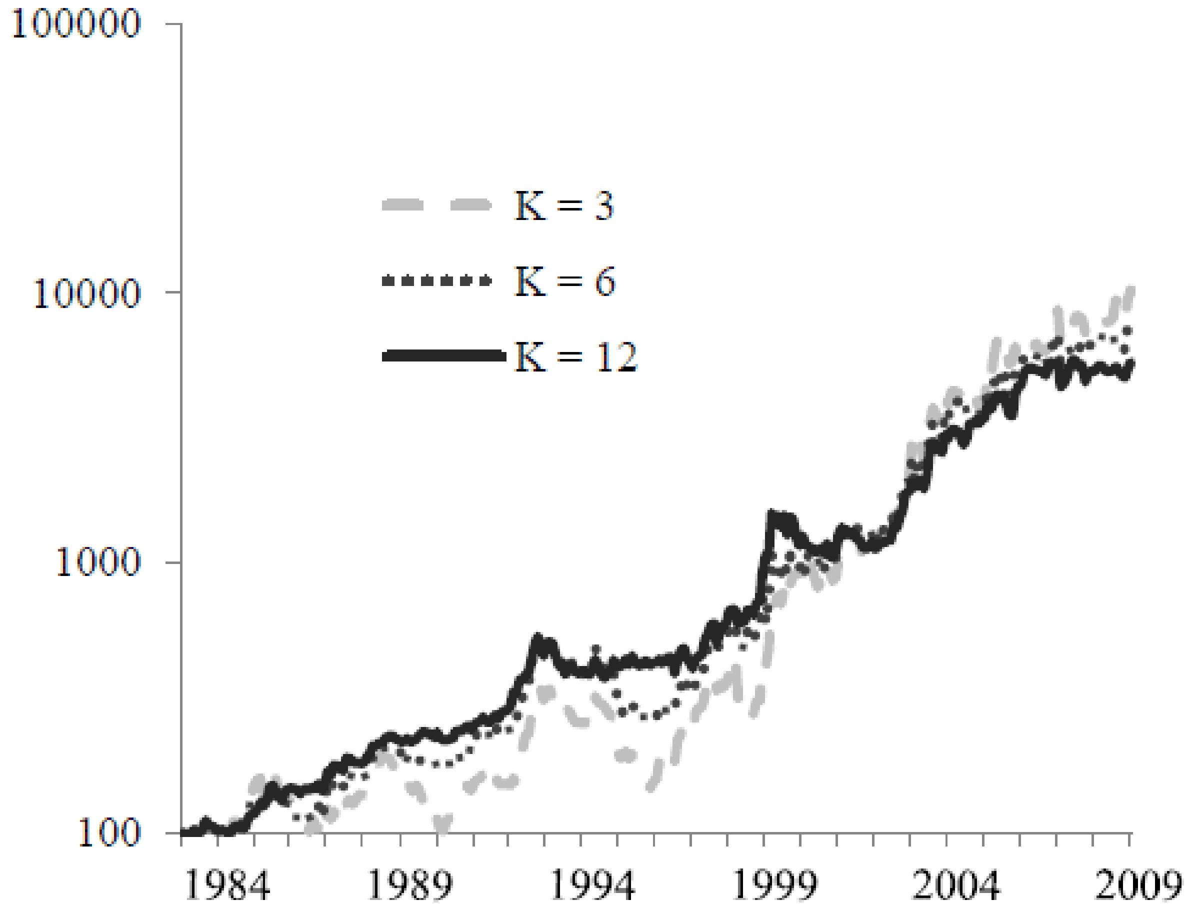
- A long position in the single strongest past winner generates a higher gross return than those generated by more diversified portfolios holding the strongest 3, 5 or 10 past winners.
- Shorting the S&P 100 Index is substantially superior as a hedge to shorting individual past loser stocks, resulting in higher gross returns and lower gross return volatility.
- Momentum strategies that are long (short) the single strongest past winner (S&P 100 Index) generate average monthly gross returns of 1.16% to 2.05%.
- The 6-month ranking period produces the largest gross returns and highest gross Sharpe ratios (see the charts below).
- Translating gross returns to net:
  - One-way trading friction of 0.2% decreases gross monthly returns by about 0.16%, 0.10% and 0.07% for holding periods of 3, 6 and 12 months, respectively.
  - The strategy with the highest average gross monthly return, 6-month ranking and 3-month holding periods, remains significantly profitable (positive) for one-way trading friction up to 0.75% (1.93%). The strategy with the highest annual gross Sharpe ratio, 6-month ranking and 12-month holding periods, remains significantly profitable (positive) for one-way trading friction up to 1.33% (3.16%).
- Results are generally robust to adjustment for market, size and book-to-market factors and for various macroeconomic indicators.

The following chart, constructed from data in the paper, summarizes annual gross Sharpe ratios across different combinations of ranking and holding periods for the best-performing level of diversification, long (short) the single strongest past winner (S&P 100 index), over the period

1984 through 2009. Results indicate that a 6-month ranking period outperforms other ranking periods and that longer holding periods outperform shorter ones. Longer holding periods have the additional advantage of lower trading frictions over the long run.



The next chart, taken from the paper, compares the gross cumulative performances of momentum strategies based on the best diversification approach (long the strongest past winner and short the S&P 100 Index) and the best ranking period (6-month) for holding periods of 3, 6 and 12 months over the entire 1984-2009 test period. Results suggest that momentum is stronger during the second half of the sample period than during the first half. While the strategy with the 3-month holding period has the highest terminal value, it also has the highest volatility and the weakest performance during the first half of the sample period.



In summary, *evidence from straightforward tests indicates that a simple momentum strategy that is long (short) the strongest past winner from the S&P 100 Index (the index itself) generates economically and statistically significant returns over the past 26 years.*

Reservations about this conclusion are:

- Testing of multiple variations of ranking period, holding period and number of stocks (along with other variations) incorporates data snooping bias, such that the best strategy combination likely overstates reasonable performance expectations.
- The measurement approach in the paper, with monthly formation of portfolios that overlap in time (and may hold the same stock at the same time) and annual rebalancing across categories (strands) of portfolios defined by holding periods, implicitly incorporates diversification that an implementing investor is unlikely to achieve. The authors report that eliminating duplicate holdings and omitting the annual rebalancing substantially lower gross returns across strategy variations.
- The authors (understandably) translate gross to net returns via static levels of trading friction. In fact trading friction varied considerably over the sample period (see "Trading Frictions Over the Long Run"). Also, for much of the sample period, there is no simple (low-cost) way to short the S&P 100 Index. The market may adapt to the decline in trading friction over the past two decades by more aggressively exploiting known sources of gross outperformance, thereby suppressing net outperformance.
- The measure of statistical significance used in the paper assumes a normal distribution of stock returns. To the extent the actual return distribution is wild, this test is not informative.

Originally published at http://www.cxoadvisory.com/9596/momentum-investing/highly-simplified-momentum-strategies/ on October 26, 2010.

Combining Momentum and Asset Growth

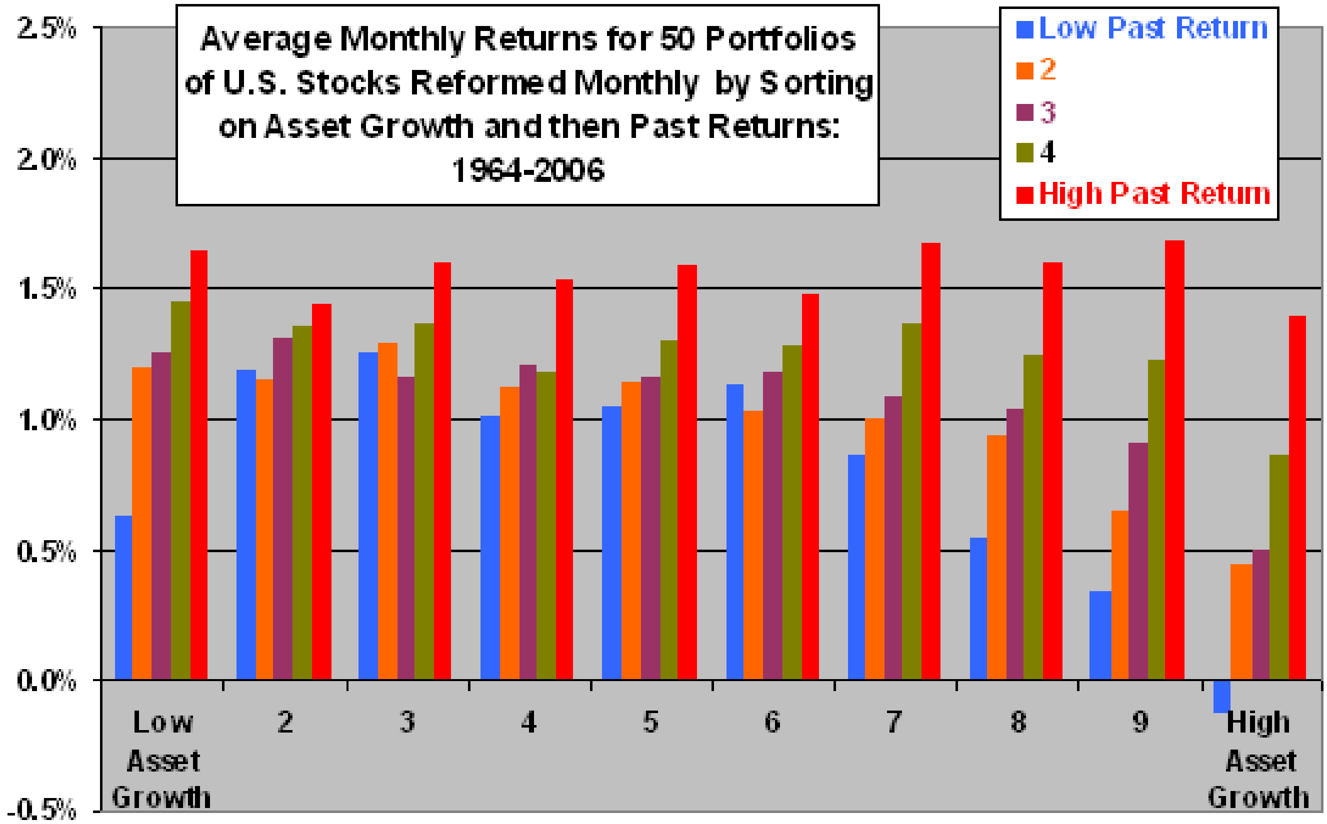
October 4, 2010

Both stock price momentum and asset growth rate exhibit empirical value as return predictors for individual stocks. Does combining these indicators offer enhanced value to investors? In their September 2010 paper entitled "Firm Expansion and Stock Price Momentum", Peter Nyberg and Salla PÃ¶yry investigate the interaction between firm-level asset growth (change in balance sheet total assets) and stock price momentum. Specifically, they measure returns for a monthly strategy that buys (sells) the prior winners (losers) within groups of stocks sorted first on on asset growth rates and then on 11-month past returns with skip-month. Using data for a broad sample of U.S. firms listed on NYSE, AMEX and NASDAQ over the period 1964-2006, *they find that:*

- Profits for hedged momentum strategies (long winners and short losers) concentrate within firms with large past asset expansions or contractions (see the chart below). Equally weighted portfolios with the highest / close to zero /lowest lagged asset growth rates generate average monthly hedged momentum strategy returns of 1.52% / 0.26% / 1.03%, respectively.
- This relationship between change in assets and momentum significantly persists after controlling for market capitalization, book-to-market ratio, share turnover, stock return volatility and credit rating. It also persists during recessions, after periods of negative lagged stock market returns and after periods of low investor sentiment.
- The firm-level relationship translates to a positive relationship between aggregate corporate asset growth rate and hedged momentum strategy performance. Subperiods characterized by exceptionally high (low) aggregate asset growth rates correspond to monthly hedged momentum strategy profitability of about 1.74% (0.18%).
- In some respects, lagged asset growth explains momentum returns better than past returns.

The following chart, constructed from data in the paper, summarizes average monthly returns for 50 equally weighted portfolios reformed monthly based on sorting first into ten groups by total asset growth rate the prior year and then into five subgroups by stock returns over the past 11 months (with skip-month) over the entire 1964-2006 sample period. Notable results are:

- High (very positive) asset growth rates enhance hedged momentum strategy returns more strongly than very low (negative) asset growth rates.
- Asset growth rate is not a future return discriminator among stocks with high past returns (asset growth rate does not enhance a long-only momentum strategy).



Note that all return calculations in this study assume frictionless portfolio formation.

In summary, *investors employing stock-level hedged (but* *<u>not</u>* *long-only) momentum strategies may be able to enhance returns by focusing on companies with high total asset growth rates the prior year.*

Originally published at http://www.cxoadvisory.com/8927/fundamental-valuation/combining-momentum-and-asset-growth/ on October 4, 2010.

Extending Value and Momentum to Frontier Market Stocks

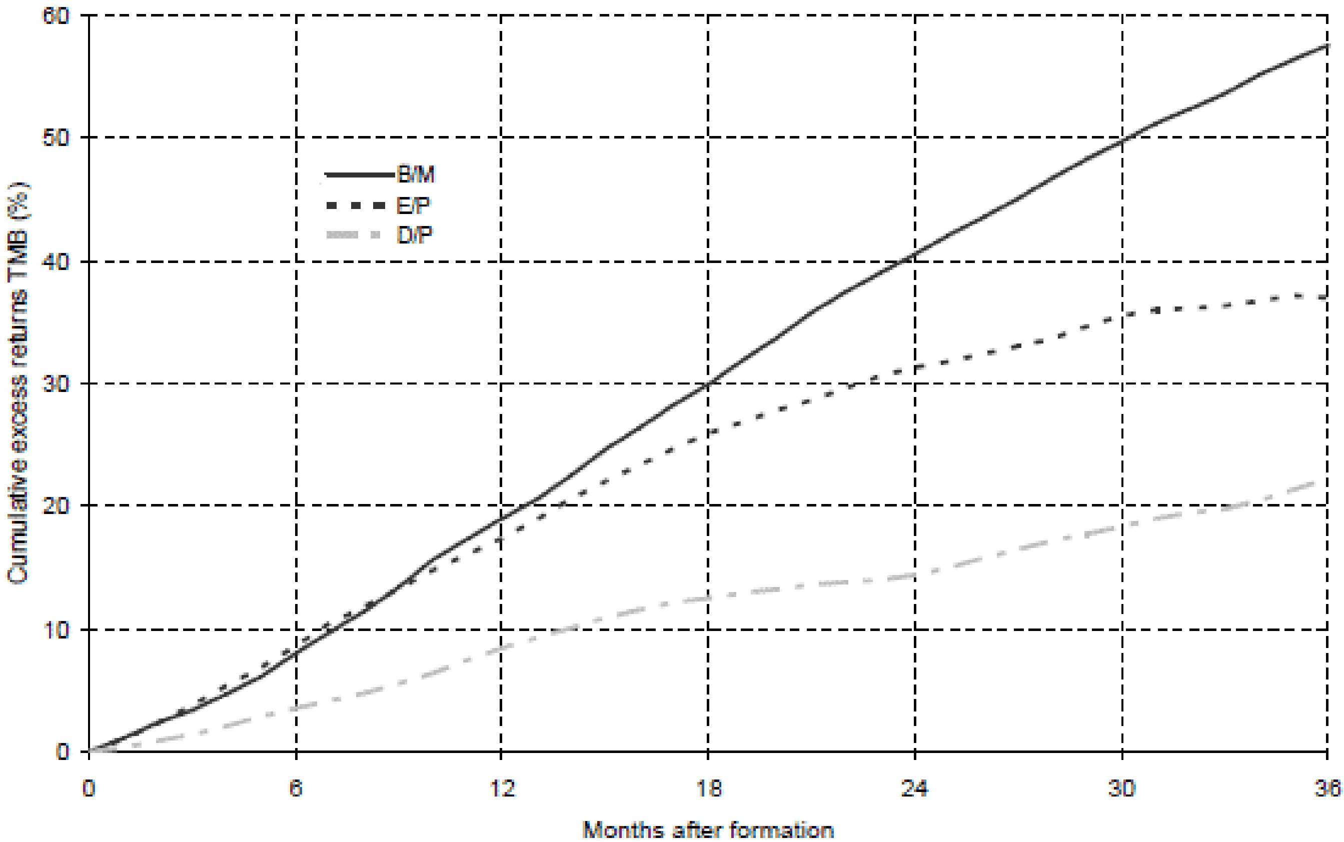
September 28, 2010

Do value and momentum strategies work in the least mature equity markets? In the September 2010 update of their paper entitled "Value and Momentum in Frontier Emerging Markets", Wilma de Groot, Juan Pang and Laurens Swinkels examine whether the value premium based on book-to-market ratio (B/M), earnings-to-price ratio (E/P) or dividend-to-price ratio (D/P) and the momentum effect exist in frontier equity markets. Their basic methodology is to form long-short portfolios of equally weighted extreme (most and least attractive) quintiles monthly and to hold each portfolio for six months, with monthly outcomes calculated as averages for the six active portfolios (in excess of U.S. Treasury bills). Using return and accounting data for over 1,400 S&P Frontier Broad Market Index stocks from 24 of the most liquid frontier markets over the period January 1997 through November 2008, *they find that:*

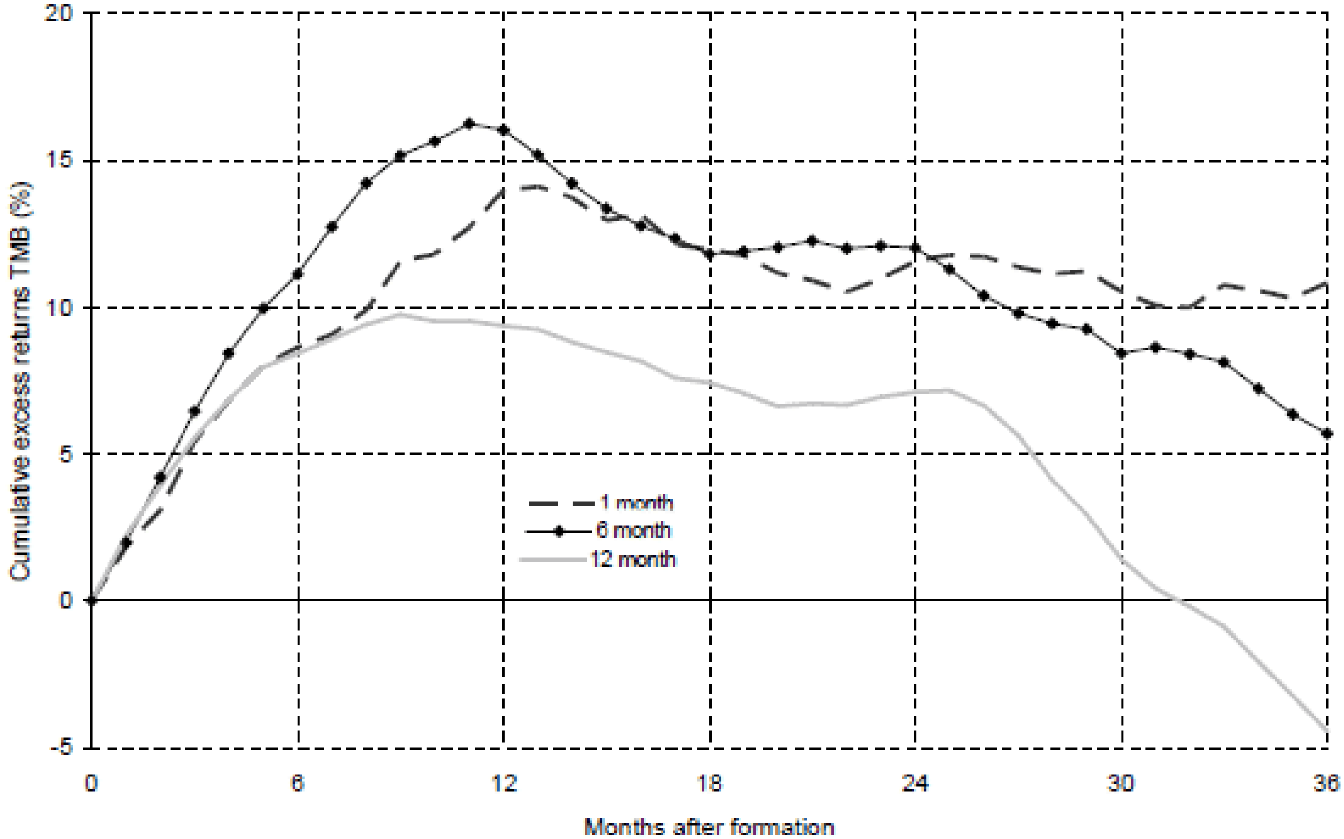
- Over the entire sample period, the average monthly equal-weighted return (standard deviation of monthly returns) of the 24 frontier markets is 0.82% (4.1%), compared to 0.53% (4.4%) and 0.64% (7.2%) for developed and more mature emerging markets, respectively. While individual frontier country market volatilities range above 15%, the low volatility of the group derives from low correlations among them.
- Portfolios from from top-minus-bottom quintiles sorted on B/P, E/P and D/P generate average excess gross monthly returns of 1.40%, 1.53% and 0.59% per month, respectively. The excess return of the B/M portfolios derives almost equally from the long and short sides, while the long sides drive excess returns for the E/P and D/P portfolios.
- Portfolios from top-minus-bottom quintiles sorted on six-month past returns generate an average excess gross monthly return of 1.69% over a six-month holding period, about two-thirds of which comes from the long sides. Cumulative returns peak at about 12 months (see the second chart below).
- Both the value premium and the momentum effect are reasonably robust to regional/country influences, liquidity and portfolio formation rule variations.
- Value and momentum strategies within the group of frontier markets correlate negatively, offering mutual diversification.
- Value and momentum strategies for the group of frontier markets generally correlate negatively with corresponding strategies in developed and more mature emerging markets, offering diversification for a global portfolio.

The following two charts, taken from the paper, summarize average cumulative returns for value and momentum hedge (top-minus-bottom quintiles – TMB) portfolios formed monthly across frontier markets during January 1997 through October 2008.

The first chart shows that portfolios that are long (short) the fifth of stocks with the highest (lowest) B/M, E/P and D/P on average continue to appreciate for at least three years after formation, with B/M offering the best long-term performance.



The second chart shows that portfolios that are long (short) the fifth of stocks with the highest (lowest) one-month, six-month and 12-month past returns on average continue to appreciate for one year or less and then exhibit reversion.



As described by the authors, collection and grooming of the data required to implement these strategies for frontier markets is cumbersome, and shorting of stocks in these markets is problematic.

In summary, *evidence indicates that the value premium and momentum effect exist at a gross level among frontier market stocks and that these anomalies are both mutually diversifying and diversifying for a global portfolio.*

Note that trading frictions would materially degrade the returns presented.

Originally published at http://www.cxoadvisory.com/8622/value-premium/extending-value-and-momentum-to-frontier-market-stocks/ on September 28, 2010.

Parsing Reversal and Momentum Effects

September 22, 2010

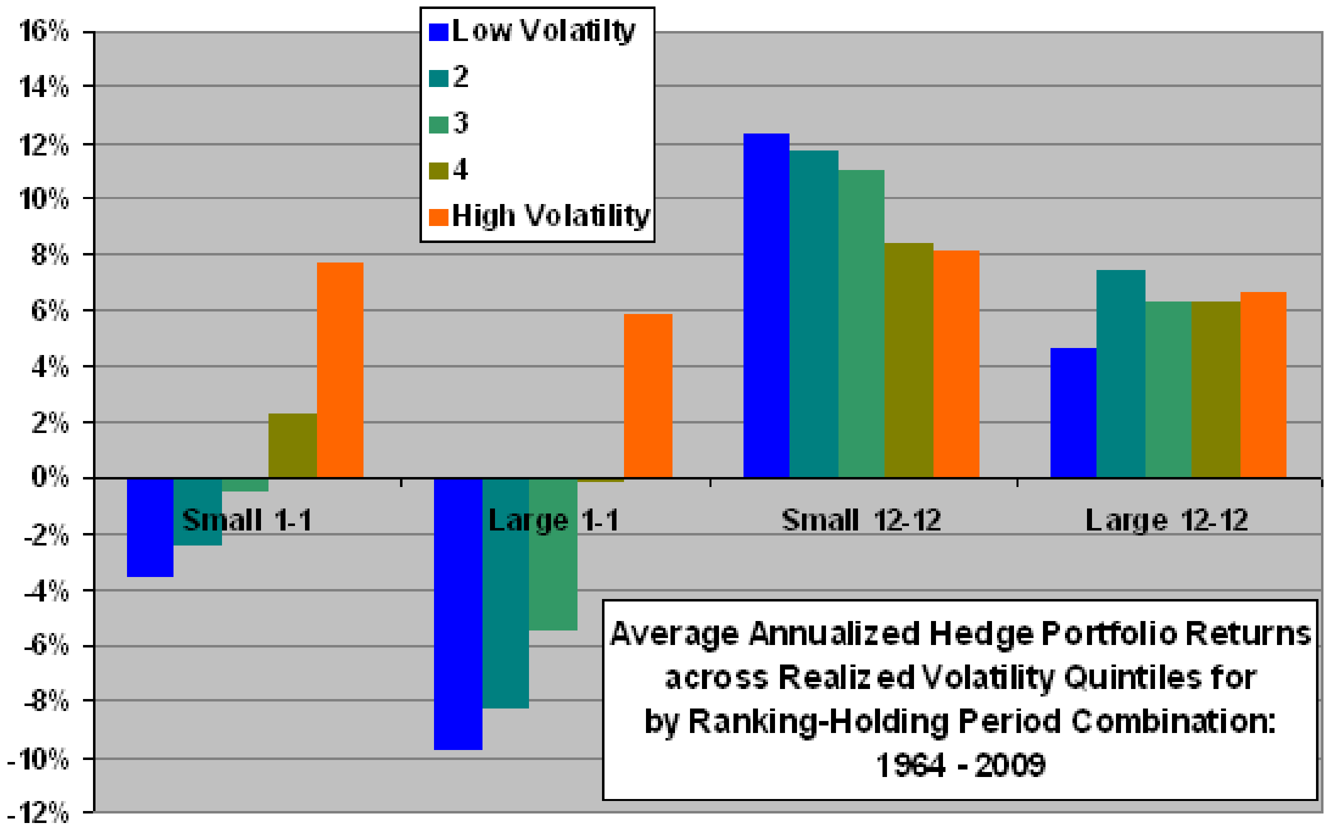
Generalizations from the body of equity price trend research are: (1) stocks tend to exhibit short-term reversal, intermediate-term momentum and long-term reversion; and, (2) small capitalization and high-volatility stocks tend to exhibit the strongest momentum. What about the combination of size and volatility? In the September 2010 version of his paper entitled "Do Momentum and Reversals Coexist?", Jason Wei investigates how momentum and reversal effects for individual stocks vary jointly with market capitalization and volatility. He forms portfolios monthly based on sequential size, realized volatility and past return sorts. He considers quintile ranking and holding periods of one, two, three, six and 12 months, with an intervening skip-week. Using daily price data for a broad sample of NYSE/AMEX/NASDAQ stocks spanning 1964-2009, *he finds that:*

- For the entire sample and sample period, there is little evidence of a one-month return reversal, and the generally positive relationship between past and future returns is not monotonic.
- Small stocks do not exhibit statistically significant reversal for any combination of volatility and horizon.
- Large stocks with low (high) return volatility exhibit reversal (momentum) over horizons of one to three months. For stocks exhibiting reversal, reversal intensity decreases as the sum of evaluation and holding periods increases.
- All combinations of size and volatility exhibit momentum at the 12-month horizon.
- Results are robust to subperiods, using three-factor (market, size, book-to-market) alphas rather than raw returns, using idiosyncratic rather than total return volatility, excluding January returns and various size partitions.

The following chart, constructed from data in the paper, shows the average annualized returns for four winner-minus-loser hedge portfolios formed monthly over the entire 1964-2009 sample period by sorting stocks first into small or large capitalization, then into quintiles of ranking period realized volatility and then into quintiles of ranking period return. The four portfolios are:

1. Small 1-1: stocks with less than median market capitalization based on one-month ranking and holding periods.
2. Large 1-1: stocks with greater than median market capitalization based on one-month ranking and holding periods.
3. Small 12-12: stocks with less than median market capitalization based on 12-month ranking and holding periods.
4. Large 12-12: stocks with greater than median market capitalization based on 12-month ranking and holding periods.

Results indicate that the short-term reversal effect is strongest for large stocks with low realized volatility and that 12-month momentum exists across ranges of size and realized volatility.



In summary, *evidence indicates that investors may be able to refine short-term reversal and intermediate-term momentum strategies for individual stocks by considering market capitalization and ranking period return volatility jointly.*

Originally published at http://www.cxoadvisory.com/8513/momentum-investing/parsing-reversal-and-momentum-effects/ on September 22, 2010.

Momentum and Moving Averages for Currencies

August 19, 2010

A reader asked: “Does a combination of rotation by relative strength (momentum) and moving averages, similar to that described in Mebane Faber’s *Ivy Portfolio*, work for the main currencies?”

The most relevant papers discovered via searches of the Social Science Research Network on the key word combinations “currency momentum”, “currencies momentum”, “currency moving average”, “currencies moving average” and “currencies technical analysis” are (underlining added):

> From March 2001, “Do Momentum Based Strategies Still Work in Foreign Currency Markets?”: “This paper examines the performance of momentum trading strategies in foreign exchange markets. We find the well-documented profitability of momentum strategies with equities to hold for currencies as well and to have continued throughout the 1980s and the 1990s. Our results indicate that the long/short strategy of buying the most attractive currency and shorting the least attractive currency obtains average excess returns that are significantly positive. Of particular note, the profitability to momentum strategies in foreign exchange markets has been particularly strong during the latter half of the 1990s. By examining 354 long/short moving average rules across eight currencies, we show the results are insensitive to the specification of the trading rule and the base currency for analysis. We also show that the correlations of the long/short momentum strategies using differing base currencies are very high – typically around 0.90. This would indicate that strong/weak momentum currencies relative to a base currency at a particular time are typically also strong/weak currencies relative to most other base currencies as well. Finally, using a bootstrap methodology we show that the performance is not due to a time-varying risk premium but depends on the underlying autocorrelation structure of the currency returns. In sum, the results lend further support to prior momentum studies on equities. The profitability to momentum-based strategies holds for currencies as well.”

> From October 2002, “Macromomentum: Returns Predictability in Currencies and International Equity Indices”: “This study examines momentum and reversals in currencies and international equity market indices. We find momentum in country equity market indices during the first year after the portfolio formation date and reversals during the subsequent two years. We also find momentum in currencies up to three years after the portfolio formation date but no reversals. Positive currency momentum predicts low stock index returns in the future weakening momentum and strengthening reversals in U.S. dollar-denominated stock index returns. Additional tests show that countries with positive

(negative) equity momentum experience declining (increasing) nominal federal fund rates in the first year after portfolio formation date and increasing (decreasing) interest rates in the subsequent two years. We discuss the implications of our findings for rational and behavioral theories."

From March 2009, "Value and Momentum Everywhere": "Value and momentum ubiquitously generate abnormal returns for individual stocks within several countries, across country equity indices, government bonds, currencies, and commodities. We study jointly the global returns to value and momentum and explore their common factor structure. We find that value (momentum) in one asset class is positively correlated with value (momentum) in other asset classes, and value and momentum are negatively correlated within and across asset classes. Liquidity risk is positively related to value and negatively to momentum, and its importance increases over time, particularly following the liquidity crisis of 1998. These patterns emerge from the power of examining value and momentum everywhere simultaneously and are not easily detectable when examining each asset class in isolation." [See "Combining Value and Momentum Across Asset Classes" for a deeper summary.]

Abstracts of *findings suggest that momentum, whether based on past returns or moving averages, exists to some degree for currencies. The studies appear not to address combining past returns and moving averages to predict currency market returns.*

Exchange-traded funds for currencies have generally not been around long enough to support testing at intervals normally used for momentum.

Originally published at http://www.cxoadvisory.com/8016/technical-trading/momentum-and-moving-averages-for-currencies/ on August 19, 2010.

Momentum Timing of Junk Bond Fund?

August 11, 2010

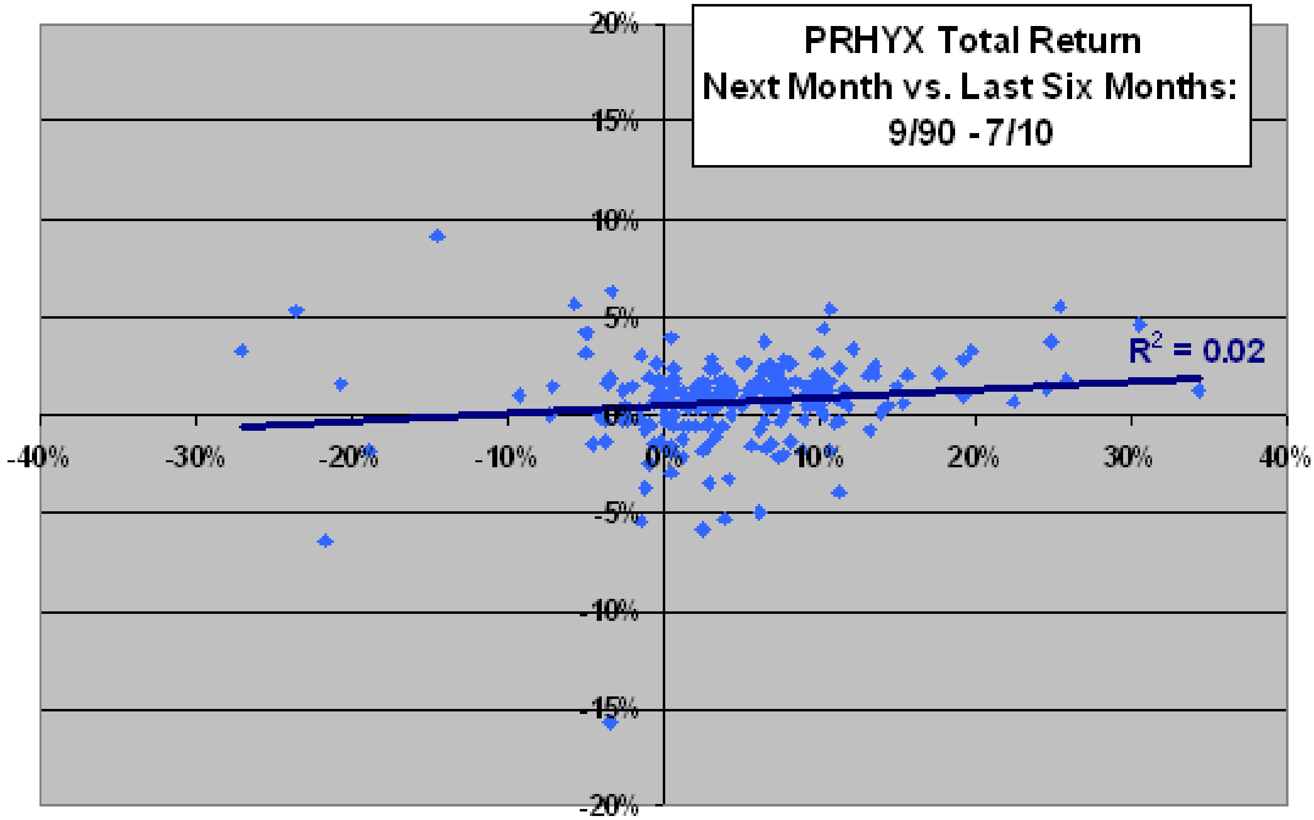
A reader commented and suggested: “Because bond trading costs would probably dwarf the excess profits described in ‘Momentum in U.S. Corporate Bond Returns’ for individual investors, perhaps the relevant question is whether switching from one junk bond fund to another based on 6-month momentum (with one skip-month) is effective.” Since the momentum in this case belongs to an asset class (junk bonds) rather than to specific bonds within it, a more useful investigation might be whether one should get in and out of junk bond funds based on momentum. Using monthly dividend-adjusted closes for the T. Rowe Price High-Yield mutual fund (PRHYX) and the 13-week Treasury bill (T-bill) yield (a proxy for return on cash) during September 1990 through July 2010 (239 months), *we find that:*

The following scatter plot relates PRHYX total return next month to PRHYX total return over the last six months over the entire sample period. The Pearson correlation for the relationship is 0.14, and the R-squared statistic is 0.02, indicating that past return explains 2% of the next-month return. Inserting a skip-month reduces the correlation to 0.03 and R-squared to 0.00 over the entire sample period, suggesting that use of a skip-month is not helpful.

Note that a sample of only 40 non-overlapping six-month return intervals, with some intervals of extreme variability in monthly returns (especially late 2008 through early 2009, does not promise reliability. For example:

- Excluding the single monthly return of April 2009 (paired with the past return for September 2008 through March 2009) increases R-squared to 0.04.
- Over the first half of the sample period (ending October 2000), the correlation is 0.20 and R-squared is 0.04. Over the second half, the correlation is 0.12 and R-squared is 0.01.

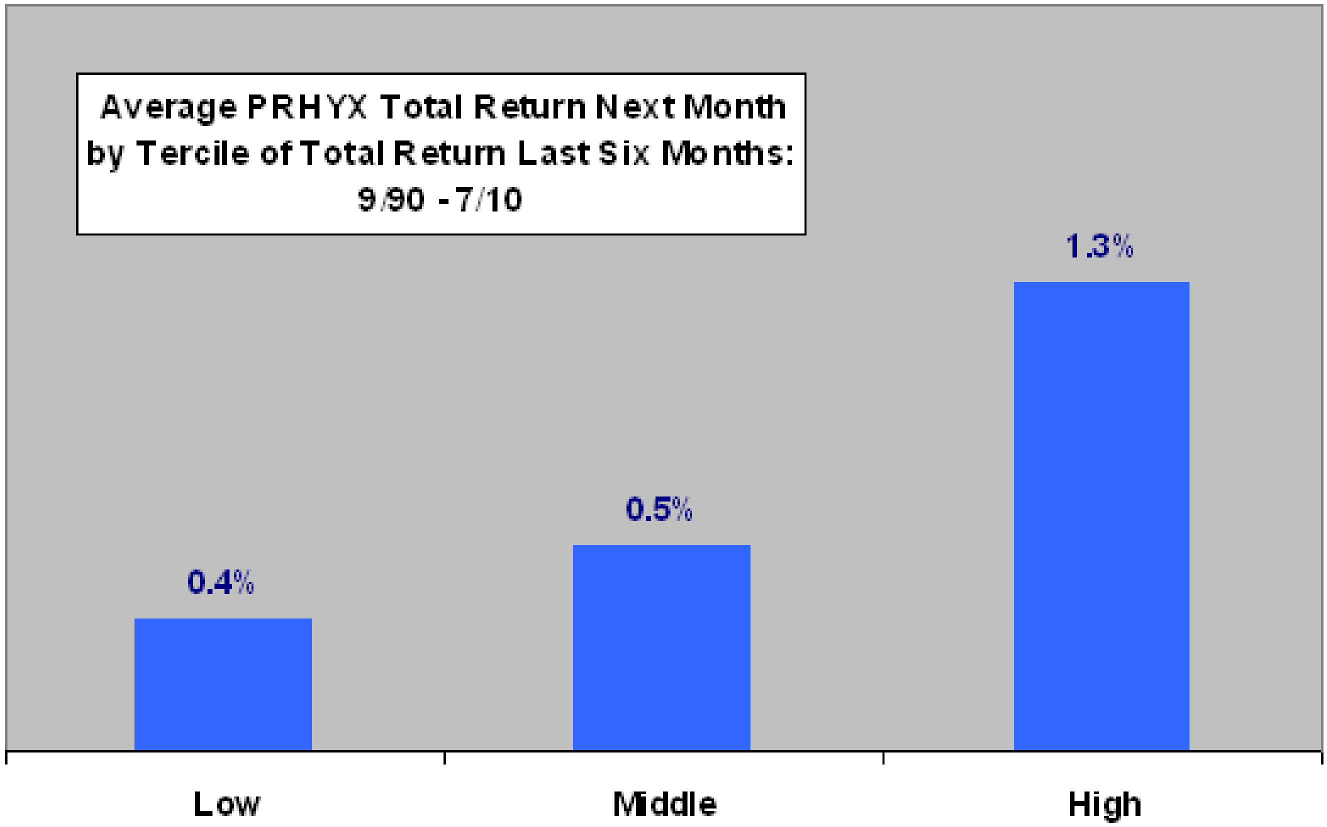
For another perspective that accommodates non-linearity, we try a ranking approach.



The next chart summarizes PRHYX average total return next month by tercile of PRHYX returns for the past six months over the entire sample period (no skip-month). The number of observations in each tercile is 77-78. Results offer support for a belief that return momentum exists for an investable collection of junk bonds.

The standard deviation of monthly returns within the lowest tercile is much higher than those within the other two.

Could a trader have beaten buying and holding the fund by using momentum measurements to switch between the fund and cash?



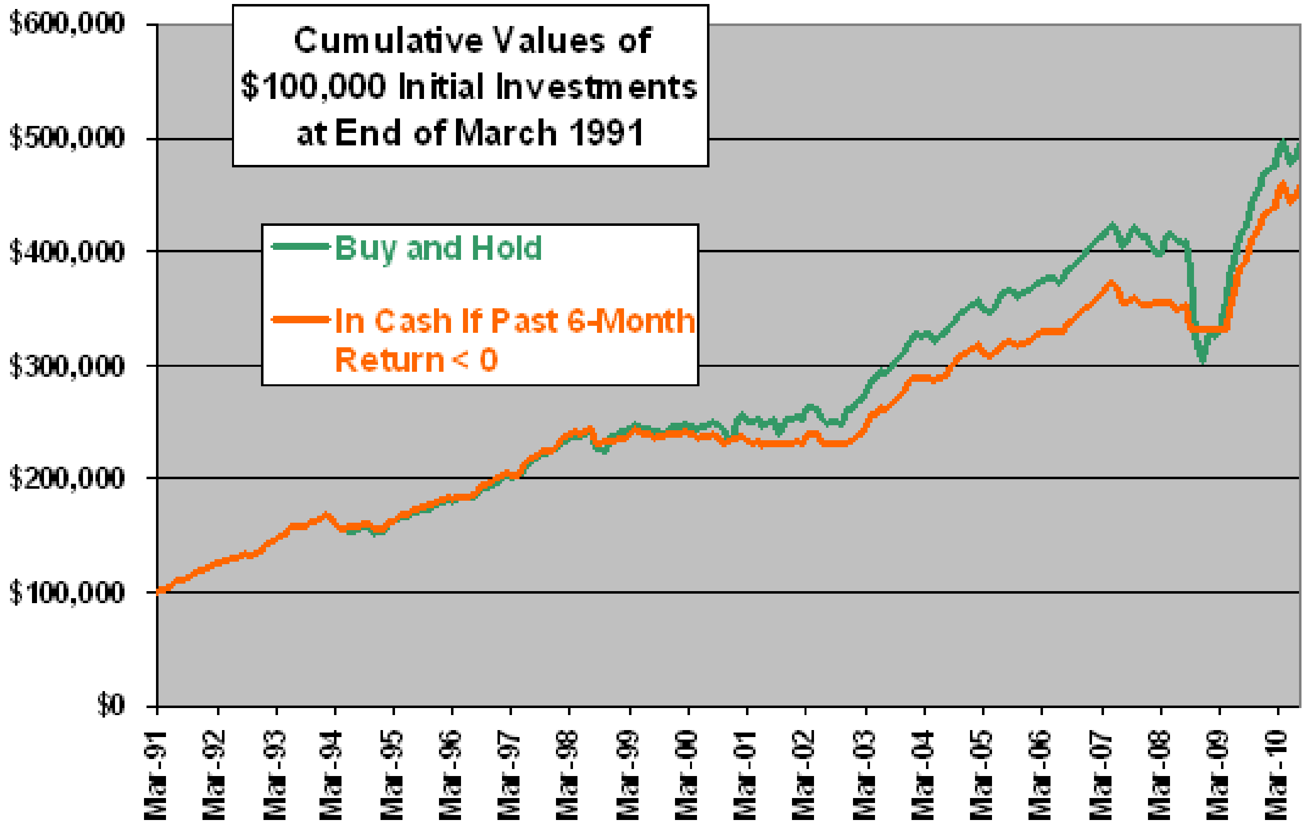
The final chart compares cumulative values of $100,000 investments initiated at the end of March 1991 for two strategies:

1. Buying and holding PRHYX.
2. Holding PRHYX (cash, with a return equal to that of T-bills) when the fund's total return over the past six months is positive (negative). The 0% past return threshold is arbitrary.

Calculations assume trades occur at month ends, coincident with momentum measurements. Such anticipation is somewhat problematic with mutual funds, priced only daily after the close. Calculations also assume no trading frictions or tax implications.

Results suggest that switching between the fund and cash roughly matches or slightly underperforms buying and holding the fund. For past return thresholds in the range of 3-5%, switching between the fund and cash marginally beats buying and holding the fund. An investor operating in real time would not know the optimum threshold (but might choose a threshold based on the historical risk-free rate rather than 0%).

Overall, results suggest that junk bond mutual fund momentum may not support outperformance when the only asset choices are the fund and cash. However, junk bond fund momentum may support multi-asset class allocation strategies such as those described in "A Few Notes on The Ivy Portfolio", "The Decision Moose Asset Allocation Framework" and "An Investor's Asset Class Momentum Trading Strategy".



In summary, *evidence from simple tests suggest that junk bond mutual funds exhibit return momentum perhaps exploitable via a multi-asset class allocation strategy (but not a standalone timing strategy).*

Originally published at http://www.cxoadvisory.com/7823/momentum-investing/momentum-timing-of-junk-bond-fund/ on August 11, 2010.

Factor Universality?

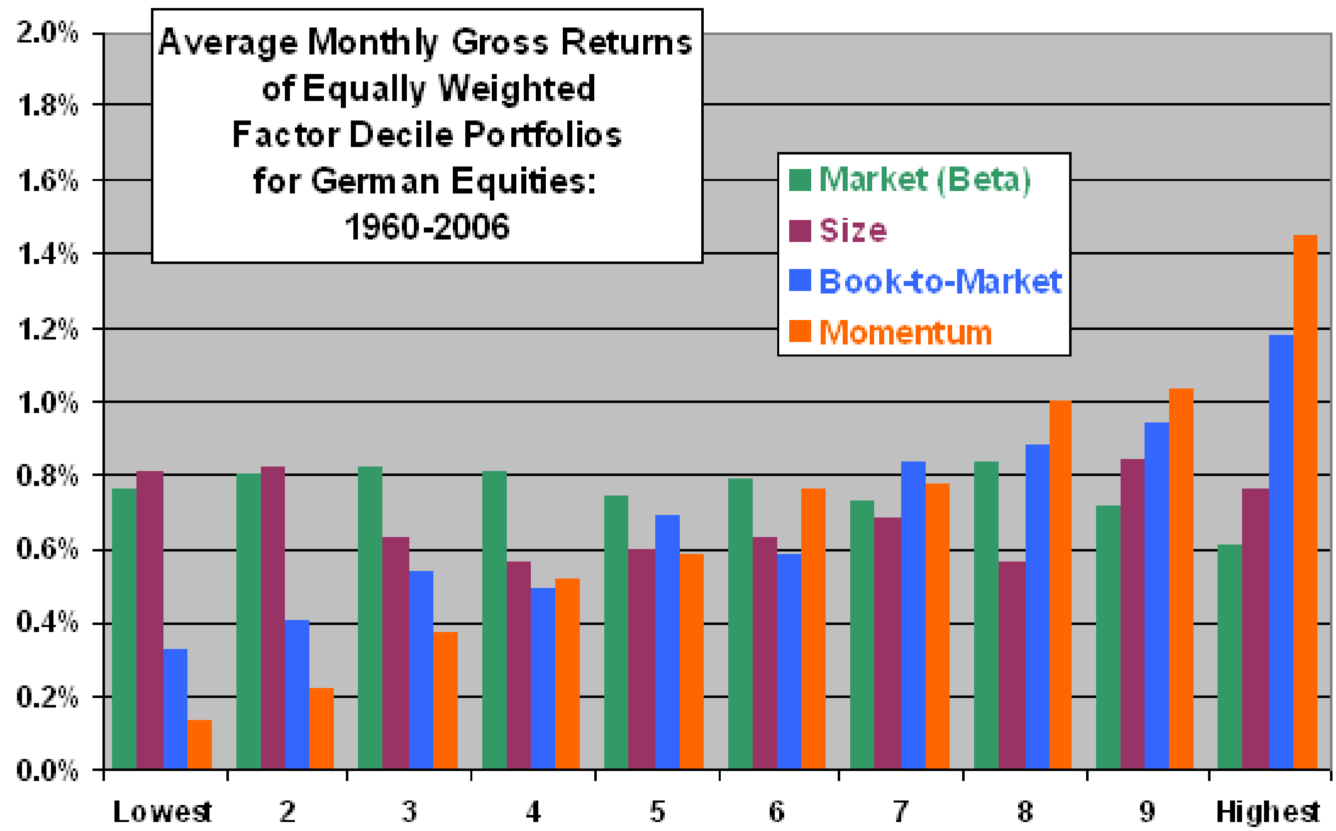
August 10, 2010

Studies of the U.S. stock market indicate that some factors and indicators may have predictive power for future returns. Do these findings consistently translate to other large equity markets? In the July 2010 version of their paper entitled "The Cross-Section of German Stock Returns: New Data and New Evidence", Sabine Artmann, Philipp Finter, Alexander Kempf, Stefan Koch and Erik Theissen apply a new set of single-sorted and double-sorted factor portfolios based on market beta, size, book-to-market ratio and momentum to test for beta effect, size effect, value premium and momentum in the German equity market. In the July 2010 version of their paper entitled "The Impact of Investor Sentiment on the German Stock Market", Philipp Finter, Alexandra Niessen-Ruenzi and Stefan Ruenzi test the predictive power of a composite sentiment measure combining consumer confidence, net equity mutual funds flow, put-call ratio, aggregate trading volume, initial public offering (IPO) returns, number of IPOs and aggregate equity-to-debt ratio of new issues. Using data for 955 non-financial German firms for which sufficient data is available during the period 1960-2006 for the factor portfolios and 1993-2006 for the sentiment measure, *these studies find that:*

"The Cross-Section of German Stock Returns: New Data and New Evidence" informs beliefs as follows:

- There is no basis for belief that stock beta or firm size predict future returns.
- There is some basis for belief that book-to-market ratio predicts future returns.
- There is strong basis for belief that momentum predicts future returns.
- The best (worst) performance among 96 double-sorted quartile portfolios comes from that comprised of stocks with the highest (lowest) momentum and highest (lowest) book-to-market ratio, generating an average monthly gross return of 1.33% (-0.10%). The associated hedge portfolio gross monthly spread of 1.43% translates to an annualized return of 17%.

The following chart, constructed from data in the paper, summarizes average monthly gross returns for equally weighted decile portfolios of German stocks based on market (beta), size, book-to-market and momentum factors over the entire sample period. Market, size, and book-to-market portfolios are reformed at the end of June of each year and held for 12 months, while momentum portfolios are reformed monthly based on return over the past 11 months lagged by one month. Results suggest that momentum has the strongest, most consistent predictive power, followed by book-to-market ratio, while the market beta and size effects are absent.



<u>"The Impact of Investor Sentiment on the German Stock Market"</u> informs beliefs as follows:

- Investor sentiment has <u>no</u> predictive power for overall stock market returns.
- Sentiment has <u>weak</u> predictive power for the difference in future returns between stocks that are arguably sentiment-sensitive (high idiosyncratic volatility, small average trade size, young, small, unprofitable, no dividend) and stocks that are arguably sentiment-insensitive.
    - This effect derives mostly from relative undervaluation of sentiment-sensitive stocks after periods of very low sentiment (consistent with investors reacting more strongly to bad news than good news).
    - Sentiment-sensitive stocks underperform sentiment-insensitive stocks for a few months after instances of very low sentiment, but then outperform in the following quarters.
- Findings are consistent with the hypothesis that retail investors are more emotional than institutional investors and the fact that retail investing comprises a relatively small fraction of trading in German stocks.

Neither study considers trading frictions in portfolio formation and adjustment.

In summary, *evidence from German stocks supports belief in the pervasiveness of a momentum effect and perhaps a value premium, but not market beta and size effects. Any sentiment effect is likely weak, specific to susceptible stocks and concentrated in intervals after very low sentiment.*

<u>Data snooping bias</u> is a suspect when cross-market findings conflict.

Originally published at http://www.cxoadvisory.com/7806/size-effect/factor-universality/ on August 10, 2010.

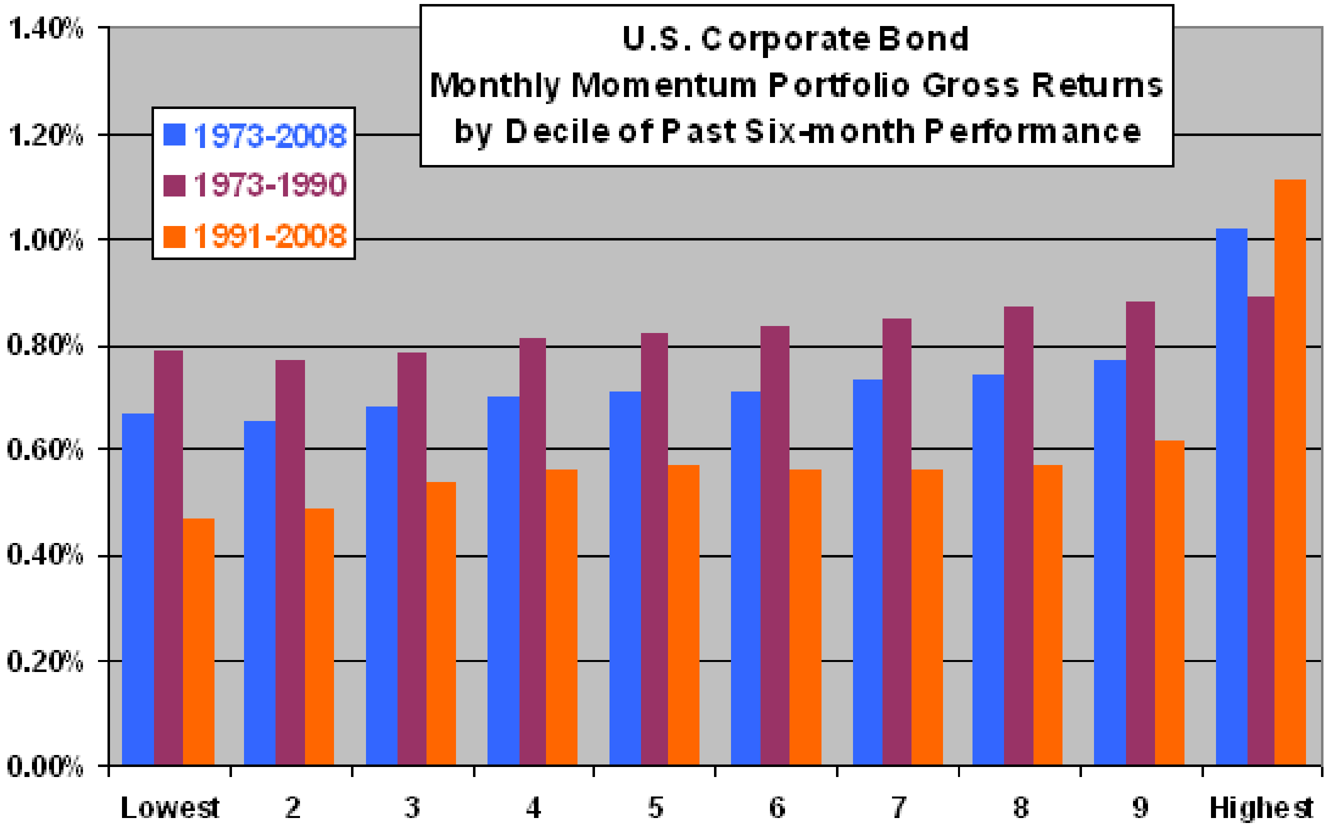
Momentum in U.S. Corporate Bond Returns

August 6, 2010

Do corporate bond returns, like stock returns, exhibit intermediate-term momentum? In their July 2010 paper entitled "Momentum in Corporate Bond Returns", Gergana Jostova, Stanislava Nikolova, Alexander Philipov and Christof Stahel measure return momentum for U.S. corporate bonds. They form equally-weighted momentum portfolios monthly based on past six-month return, with a skip-month between ranking interval and portfolio formation to avoid short-term reversal, holding each portfolio for six months. Using total returns associated with 3.2 million quotes and transactions for 77,150 bonds over the period 1973-2008, *they find that:*

- The mean (median) monthly total return for bonds in the sample is 0.66% (0.62%).
- About 82%of rated bonds are investment grade (BBB- or above), and 18% are non-investment grade.
- Bond momentum profitability derives from the second half of the sample period (1991-2008), during which portfolios that are long (short) the bonds with the highest (lowest) past six-month return generate an average gross monthly return of 0.64%. (See the chart below.)
- This momentum strategy is profitable only among non-investment grade bonds. Applied only to these low-grade bonds, the strategy yields an average gross monthly return of 1.9%, easily surviving conservative trading friction estimates to generate an average six-month netreturn of about 10%. In fact:
    - Profitability of the momentum strategy disappears after removing the worst-rated 8% of observations.
    - During 1991-2008 period, the momentum strategy generates a gross monthly return of 1.73% among the fifth of stocks with the highest credit risk, but less than 0.21% for each of the other four quintiles of credit risk.
    - The low proportion of non-investment grade bonds during 1973-1990 may explain the lack of momentum among all bonds for that subperiod. In fact, the worst-rated bonds do exhibit momentum during 1973-1990.
- Unlike equities, bond momentum profitability derives principally from past winners (see the chart below).
- While momentum is strongest among bonds with the lowest credit ratings, commonly used risk factors do not explain the anomaly. Nor do liquidity, periods around rating changes, choice of bond price database or survivorship bias substantially explain the anomaly.

The following chart, constructed from data in the paper, shows average gross monthly returns of U.S. corporate bonds by decile of past six-month returns (constructed and measured as described above) over the entire sample period and two equal subperiods. Results indicate that: (1) momentum is largely absent in the earlier subperiod (perhaps due to the relative paucity of low-grade bonds during that time); and, (2) extreme winners drive overall results.



In summary, *evidence indicates that investors may be able to exploit momentum in U.S. corporate bond returns by focusing on past winners among low-grade issues.*

Originally published at http://www.cxoadvisory.com/7730/momentum-investing/momentum-in-u-s-corporate-bond-returns/ on August 6, 2010.

Sentiment from Google Insights and Return Continuation

July 15, 2010

Does investor interest in stocks as measured by Google Insights for Search predict which stocks will exhibit return continuation? In his June 2010 paper entitled "The Demand for Information", Gordon Sims examines the effects of investor attention to stocks as defined by relative search frequency from Google Insights for Search (Stock Information Demand) to short-term stock momentum. The past return interval for momentum measurement is four weeks, augmented by a one-week delay in portfolio formation to avoid short-term reversal. Search term construction for Stock Information Demand focuses on intent to buy or sell a stock by appending "stock" or "quote" to a company's name or ticker symbol. Using weekly returns for July 2003 through December 2009 for those S&P 500 stocks (as of July 31, 2003) with sufficient weekly Stock Information Demand data over the period 2004-2009 (214 stocks), *he finds that:*

- Over the entire sample of stocks, there is no reliable continuation of past four-week return (plus skip-week), with or without consideration of Stock Information Demand.
- However, there are potential indications for sample subsets:
  - Stocks with high Stock Information Demand that have increased in price over the last four weeks tend to continue advancing for the next four weeks, with no subsequent reversal. This continuation is absent for past winners with low Stock Information Demand.
  - Stocks with low Stock Information Demand that have decreased in price over the last four weeks exhibit a weak tendency to continue declining over many weeks.
- Shorter and longer past return measurement intervals and different sorting thresholds yield similar results, alleviating concern about data snooping bias.
- The sample of stocks is modest and skewed toward firms with large market capitalization. The sample period is short, not accommodating measurement of momentum effects for commonly used past return intervals.

In summary, *evidence from limited tests suggests that online search activity may help identify which recent winning and losing stocks exhibit some tendency to continue winning and losing.*

Originally published at http://www.cxoadvisory.com/7064/sentiment-indicators/sentiment-from-google-insights-and-return-continuation/ on July 15, 2010.

Past Performance Consistency and Future Returns

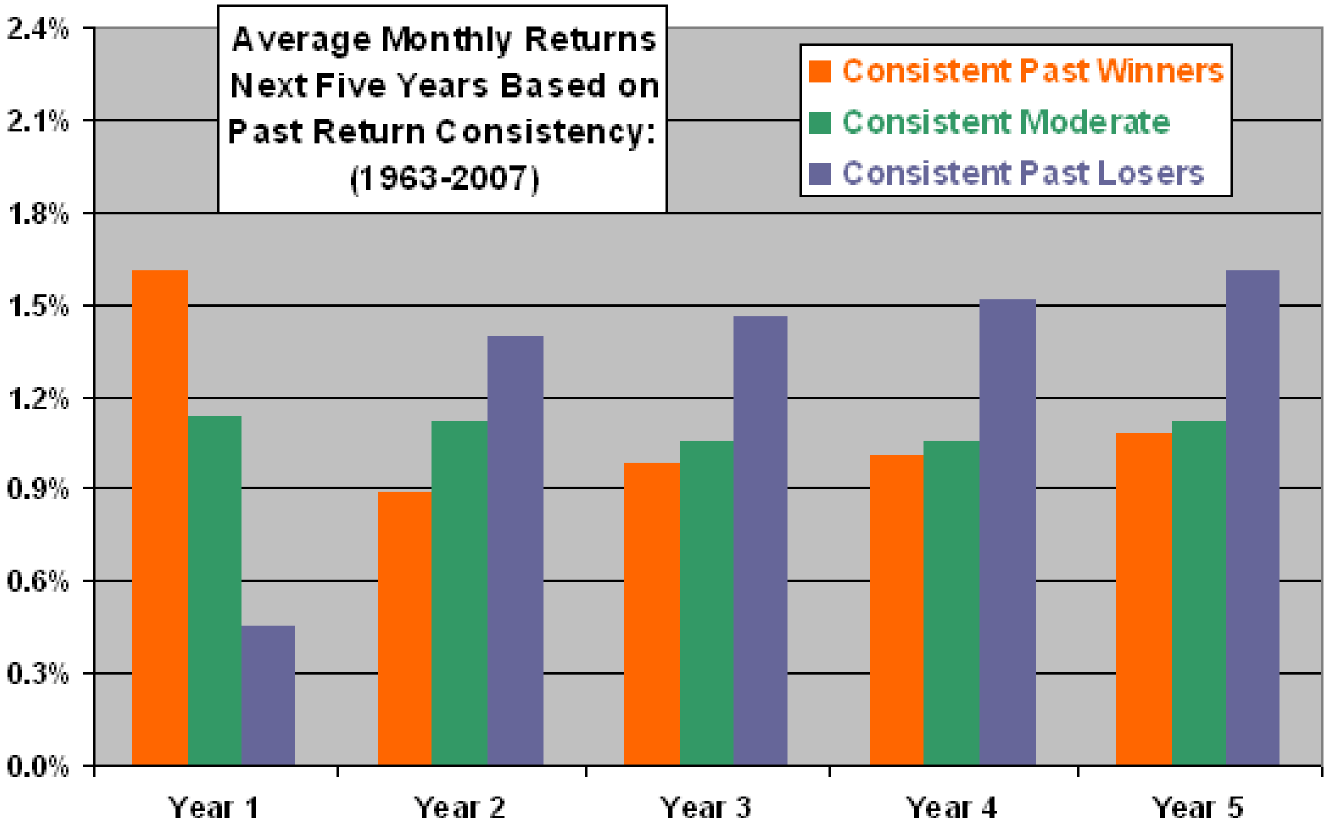
June 25, 2010

What are the momentum and reversion patterns for stocks that have been consistent past winners or losers? In his June 2010 paper entitled "Does Bad Economic News Play a Greater Role in Shaping Investors' Expectations than Good Economic News?", Abdulaziz Alwathainani investigates the relationship between the consistency of past monthly stock performance and future returns. He defines consistent past winners (losers) as those ranking in the top (bottom) 30% of monthly returns for at least six of the last 12 months. He defines stocks ranking in the middle 40% for at least six of the last 12 months as a consistently moderate benchmark. Using monthly return and characteristics data for a broad sample of U.S. stocks spanning 1963-2007, he finds that:

- Over the entire sample period, consistent losers exhibit stronger average return momentum during the first year after portfolio formation and more pronounced and persistent average return reversal in years two through five than do consistent winners (see the chart below).
  - During the first year after portfolio formation, the consistent winner (loser) portfolio outperforms (underperforms) the benchmark consistent moderate portfolio by about 0.47% (0.69%) per month.
  - In years two through five after portfolio formation, the consistent winner (loser) portfolio marginally underperforms (substantially outperforms) the benchmark consistent moderate portfolio.
- Results generally suggest that investors overreact asymmetrically to past performance of consistent winners and losers over the intermediate term (one year) and subsequently correct asymmetrically over the long term (two to five years), with intermediate positive and long-run negative autocorrelations in returns distinct components of price evolution.
- The consistent loser portfolio exhibits a strong counter-tendency (gain) in January of the first year after formation. The bulk of long-term return reversal concentrates in January, particularly for the consistent loser portfolio.
- Results are robust to the Fama-French three-factor (market, size, book-to-market) model and the momentum factor. Specifically, the momentum factor does not subsume the ability of return consistency to predict future returns.

The following chart, constructed from data in the paper shows average monthly returns of equally weighted portfolios formed each month during January 1963 through December 2002 based on consistency of past stock returns and held without rebalancing for the next five years. Results show momentum and reversal effects, with consistent past losers exhibiting stronger intermediate-term momentum and stronger long-term reversal compared to the benchmark consistent moderate portfolio than do consistent past winners.

Results do not include any trading frictions involved in forming and liquidating portfolios.



In summary, *evidence indicates that investors may be able to exploit consistency of past stock performance, independently of widely used momentum measures, via continuation over the intermediate term and reversal over the long term.*

Originally published at http://www.cxoadvisory.com/6995/technical-trading/past-performance-consistency-and-future-returns/ on June 25, 2010.

How About Investors FastTrack?

June 11, 2010

A reader asked: “I found Investors FastTrack via a search last night. Do you know anything about them?”

Per the Investors FastTrack web site, the company offers: “dividend-adjusted, historical mutual fund, ETF, and stock data to thousands of investors worldwide; software and training to individual investors and money managers; low cost, daily updates; and, web pages, and custom applications to financial institutions.” Paul and Shirley Charbonnet founded the company in 1989.

The “simple truths” that Investors FastTrack presents and the strategy the company features are:

- “This year’s best fund is often next year’s worst fund.”
- “No fund is always the best fund.”
- “The best fund is, invariably, a sector fund.”
- “Momentum strategies work best when trading among sector funds. FastTrack’s Momentum Monthly FTAlpha Model the actual value of a portfolio once a month over many years of Momentum trading consistently beats the S&P 500 return, gaining over 20% annually”

Investors FastTrack does not provide the specifications of the FTAlpha Model or the other models they summarize. Though they use the term “actual value,” the specifications may be optimized via backtesting, thereby incorporating data snooping bias (luck) and overstating expected returns. The specifications may ignore the fees charged by Investors FastTrack for services and any fees charged by brokers for fund trading. It is arguable that the benchmark for the FTAlpha Model should be a basket of sector funds rather than an S&P 500 Index fund.

For relevant analyses of simple momentum strategies applied to sector exchange-traded funds (ETF) since the end of 1998, see:

“Simple Sector ETF Momentum Strategy Performance”

“Simple Sector ETF Momentum Strategy Robustness/Sensitivity Tests”

“Alternative Sector ETF Momentum Metrics”

“Comparison of 3:6:12-1 and 6-1 Sector ETF Momentum Strategies

“Sector ETF Momentum with Selective Shorting of Losers”

Monthly ranking of sector ETFs on six-month past returns generally produces the best results, but the second item offers some cautions.

Parts of “The NoLoad FundX Mutual Fund Momentum Approach” are also relevant.

Originally published at http://www.cxoadvisory.com/6828/momentum-investing/how-about-investors-fasttrack/ on June 11, 2010.

Momentum and Portfolio Risk

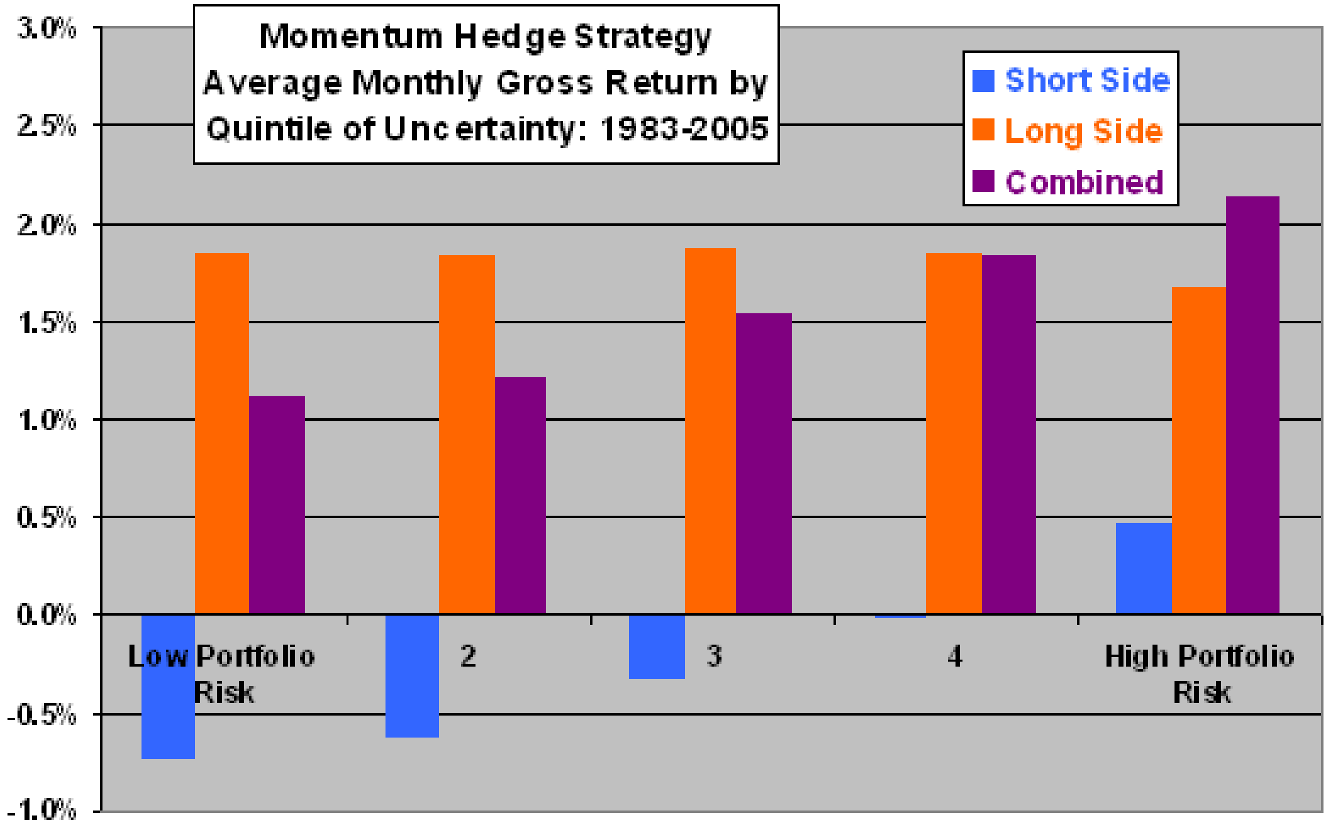
May 26, 2010

Do measures of momentum portfolio risk affect returns and return components? In their April 2010 paper entitled "Asymmetric Momentum Effects Under Uncertainty", David Kelsey, Roman Kozhan and Wei Pang investigate how the profitability of a momentum hedge strategy varies with portfolio firm-level risk. They use six measures of firm-level risk: (1) size (market capitalization); (2) age (since listing); (3) number of analysts following; (4) dispersion of analyst earnings forecasts; (5) realized volatility of weekly stock returns over the past year; and, (6) cash flow volatility. Using stock return, firm fundamentals and analyst earnings forecast data for a broad sample of U.S. stocks spanning 1983-2006, *they conclude that:*

- Momentum hedge portfolio gross return generally increases with portfolio firm-level risk for all of the six risk measures.
- Variation in return to the short side of the hedge portfolio drives the variation in momentum returns with portfolio firm-level risk (see the chart below).
- Investors may be able to tune momentum portfolio performance by weighting the long and short sides differently according to the level of portfolio risk.

The following chart, constructed from data in the paper, compares average monthly gross returns for the short side, long side and combined sides of equally weighted hedge portfolios formed from monthly double quintile sorts of the broad sample of U.S. stocks over the entire sample period. The first sort is on past 12-month return. The second sort is on one of the six measures of portfolio risk. These sorts produce 30 hedge portfolios (six measures of risk times five quintiles of uncertainty for each measure) that are long past winners and short past losers, reformed monthly. The chart presents the average returns across the six measures by quintile of risk.

Results show that the contribution of past winners to momentum hedge portfolios is insensitive to portfolio risk, but that the contribution of past losers increases from negative to positive as risk increases. Investors may want to vary portfolio winner-loser composition according to level of portfolio risk.



This study ignores trading frictions and the way in which trading frictions may vary with level of portfolio risk. Such variation might offset the effects of portfolio risk on gross return.

In summary, *evidence suggests that investors employing hedge momentum strategies may want to adjust the level of hedging (long past winners versus short past losers) according to portfolio risk level.*

Originally published at http://www.cxoadvisory.com/6427/volatility-effects/momentum-and-portfolio-risk/ on May 26, 2010.

Isolating the Decisive Momentum (Echo?)

May 6, 2010

Momentum strategies generally consider returns over past months up to one year ago in constructing signals for future abnormal returns. Is some part of that 12-month history more important than others? Might returns from more than a year ago be informative? In the November 2009 version of his paper entitled "Is Momentum Really Momentum?", Robert Novy-Marx parses the effectiveness of past returns as indicators of future returns by age from one to 15 months, focusing on: recent past return with a skip-month, six months to two month old (6-2); and, intermediate past return, 12 months to seven months old (12-7). Using data for a broad sample of U.S. stocks spanning 1926-2008 (83 years) and shorter samples for various other assets, *he concludes that:*

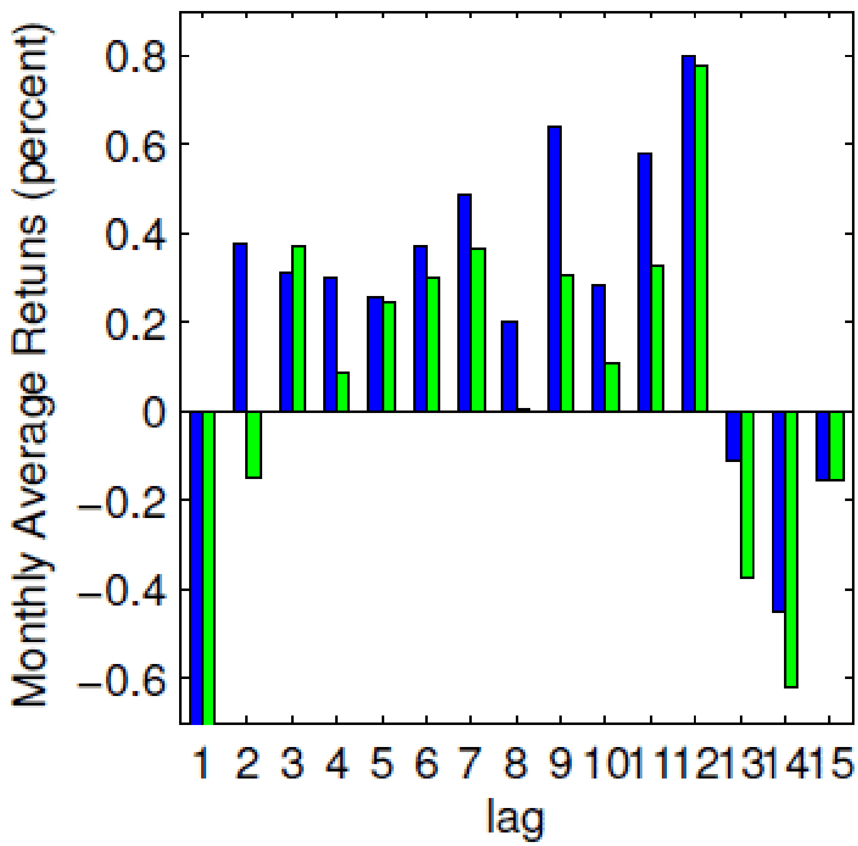
- Strategies based on 6-2 cumulative return are profitable but less so than those based on 12-7 cumulative return, especially among large-capitalization stocks.
  - Within the fifth of stocks with the largest market capitalizations, a value-weighted strategy that each month buys (sells) the top (bottom) 20% of stocks based on 12-7 return generates average annualized returns of almost 10% during 1927-2008.
- Stocks with the highest 6-2 returns but poor 12-7 returns on average significantly underperform stocks with the lowest 6-2 returns but strong 12-7 returns.
- Four-factor alpha (adjusted for market, size, book-to-market, 12-7 momentum) is insignificant for strategies based on 6-2 return.
- Since performance of strategies based on 6-2 return relates positively to performance based on 12-7 return, particularly over the past 40 years, adding information from 6-2 return does not significantly boost performance for investors already using 12-7 return.
- While the predictive power of 6-2 return appears to fade in recent decades, that of 12-7 return does not. Specifically, strategies based on 6-2 return are very profitable in the 1950s and 1960s, but not since. Strategies based on 12-7 return are consistently profitable over time, if anything more profitable over the last forty years.
- Findings apply not only to individual U.S. stocks but also to industries, styles, international equity indexes, commodities and currencies. Sharpe ratios of strategies based on 12-7 return are generally more than double those of strategies based on 6-2 return.

The following chart, taken from the paper, compares average monthly returns for momentum strategies that buy (sell) the 10% of stocks with the highest (lowest) returns during each of the 15 individual months prior to monthly portfolio formation. Dark blue (light green) bars depict value-weighted (equal-weighted) results. The average monthly value-weighted (equal-weighted) return for the truncated one-month reversals is -0.98% (-2.92%). Results indicate why:

- Momentum strategies often incorporate a skip-month to avoid the one-month reversal effect.

- Momentum strategies do not use returns older than 12 months, which indicate return reversal rather than continuation.
- Intermediate months may be the most informative about future returns.

Among combinations based on cumulative returns from 12 months ago to X < 12 months ago, the value-weighted strategy with X = 6 and the equal-weighted strategy with X = 11 generate the highest Sharpe ratios. These additional results suggest that recent past returns, essential to many explanations of the momentum anomaly, may actually contribute little to profitability.



In summary, *evidence from an array of tests indicates that the cumulative return over the period from 12 months ago to seven months ago is decisive for the momentum anomaly for U.S. stocks, industries, styles, country indexes, commodities and currencies. Including more recent, largely irrelevant past returns in forming momentum portfolios may hurt performance.*

In other words, instead of one skip-month, investors should consider six skip-months in forming “momentum” portfolios.

Study results generally do not include trading frictions. Given all the strategy combinations considered, data snooping bias may be material in some ways (but mitigated by the variety of tests).

Originally published at http://www.cxoadvisory.com/5944/momentum-investing/isolating-the-decisive-momentum-echo/ on May 6, 2010.

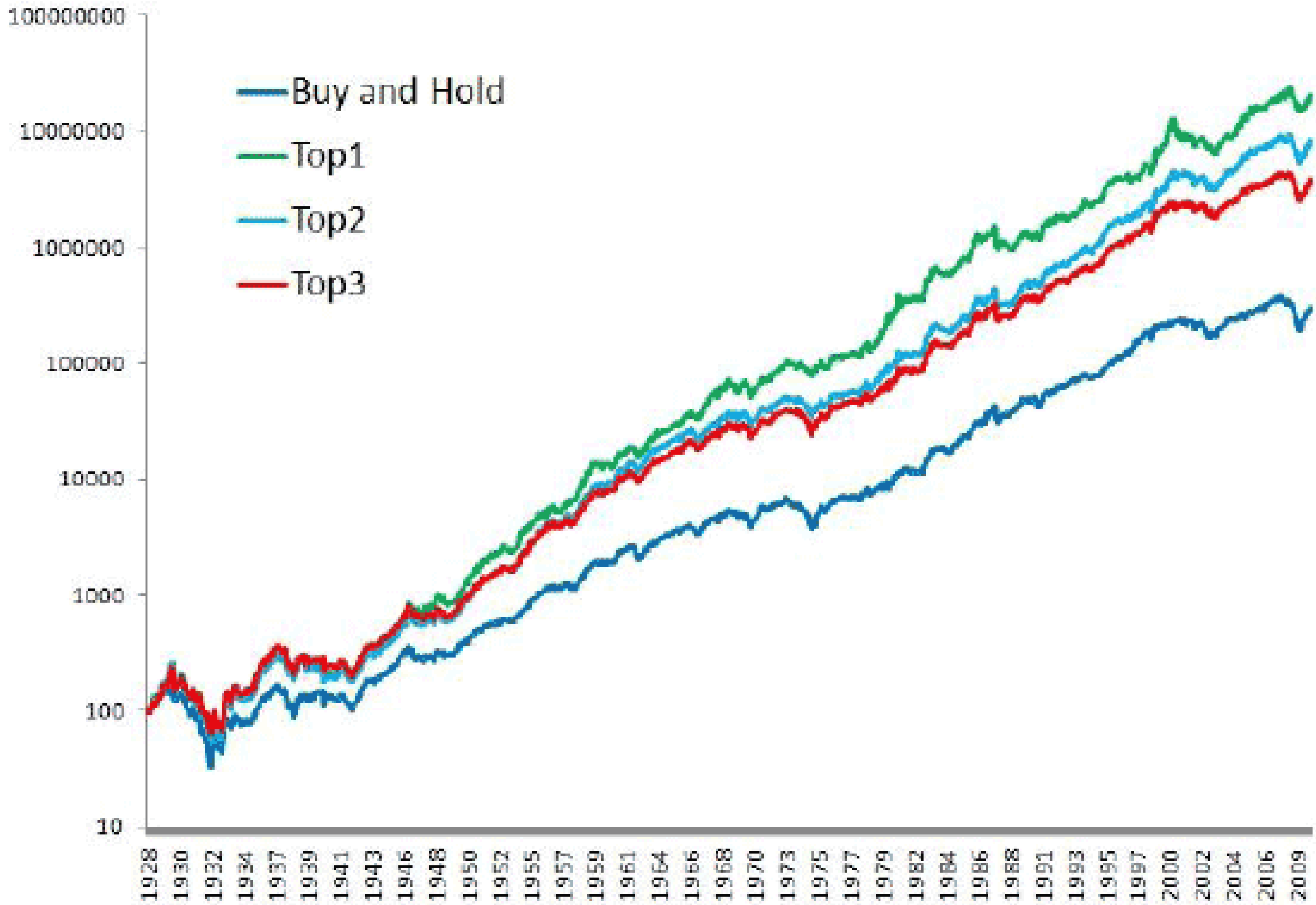
Industry/Asset Class Momentum Over the Long Run

April 26, 2010

Does the momentum anomaly hold for industries/asset classes over the long run? In his April 2010 draft paper entitled "Relative Strength Strategies for Investing", Mebane Faber quantifies the effects on gross returns of applying simple momentum/trend following rules to U.S. equity industry and global asset class portfolios. His "intent is to describe some simple methods that an everyday investor can use to implement momentum models in trading." Momentum rankings derive from trailing total returns over intervals ranging from one to twelve months, as well as a combination of multiple intervals. Using monthly levels of ten value-weighted U.S. equity industries spanning July 1926 through December 2009 and of global asset classes spanning 1973-2009, *he concludes that:*

- Momentum portfolios that invest in the top one, two or three U.S. equity industries since 1928, rebalanced monthly (see the chart below):
    - Work for all past performance ranking intervals from one month to twelve months, and for a combination of 1, 3, 6, 9 and 12-month intervals.
    - Outperform an equally weighted portfolio of all ten industries (rebalanced monthly) in about 70% of all years.
    - Outperform the equally weighted portfolio of all ten industries in all decades from the 1930s to the 2000s.
- Specifying "cash" (short-term Treasury bills) rather than equities when the "winning" industries are below their 10-month simple moving averages generally preserves the return while decreasing both volatility and drawdown of a momentum portfolio.
- Momentum portfolios that invest in top performers from a group of five relatively uncorrelated global asset classes exhibit similar outperformance and performance persistence relative to an equally weighted portfolio of all five classes (rebalanced monthly).
- A round trip trading friction of 1% for portfolio rebalancing would still allow for excess momentum profits.

The following chart, taken from the paper, compares the cumulative gross performances of momentum portfolios that invest in the top one, two or three U.S. equity industries, rebalanced monthly based on a combination of 1, 3, 6, 9 and 12-month past returns. Gross outperformance relative to an equally weighted portfolio of all ten industries (rebalanced monthly) is roughly 3%-6% per year.



In summary, *evidence from simple tests indicates that the momentum anomaly is substantial and persistent over long periods for industries/asset classes on a gross return basis.*

"Simple Sector ETF Momentum Strategy Performance" offers a relevant investigation using easily tradable U.S. equity sector exchange-traded funds since their inception in late 1998. Follow-up analyses in the "Momentum Investing" category explore robustness of this approach.

"Bypassing Trading Frictions?" offers observations about avoiding trading frictions for market timing strategies via families of mutual funds that allow free and frequent fund switching (as suggested in the paper).

Originally published at http://www.cxoadvisory.com/5688/technical-trading/industryasset-class-momentum-over-the-long-run/ on April 26, 2010.

Credit Ratings and Stock Return Anomalies

April 23, 2010

Does designated creditworthiness, closely related to riskiness, drive the performance of many widely acknowledged stock return anomalies? In the April 2010 revision of their paper entitled "Anomalies and Financial Distress", Doron Avramov, Tarun Chordia, Gergana Jostova and Alexander Philipov use portfolio sorts and regressions to investigate the relationship between financial distress (low credit ratings and downgrades) and profitability for trading strategies based on: stock price momentum, earnings momentum, credit risk, analyst earnings forecast dispersion, idiosyncratic volatility, asset growth, capital investments, accruals and value. Using data for broad samples of U.S. stocks (limited by extensive information requirements) spanning October 1985 through December 2008, *they conclude that:*

- Profitability of strategies based on price momentum, earnings momentum, credit risk, analyst earnings forecast dispersion, idiosyncratic volatility and capital investments derives predominantly from short positions in firms with poor credit during deteriorating credit conditions.
    - Profitability of these anomalies comes entirely from firms rated BB+ or lower, representing only 9.7% of sample market capitalization. However, the anomalies are reasonably robust among all size groups.
    - Profitability comes mostly from 12-month intervals bracketing credit rating downgrades.
- The asset growth anomaly exhibits similar patterns, except for very small-capitalization stocks with low credit ratings and large-capitalization stocks with medium credit ratings.
- Findings do not apply to the accruals and value anomalies.
    - The accruals anomaly (a result of management discretion concerning the gap between net profit and operating cash flows) is robust for firms of both high and low credit risk, and across deteriorating, stable and improving credit conditions.
    - The value anomaly appears to derive from long positions in low-rated firms that survive financial distress, mostly during stable or improving credit conditions.
- Firms with low credit ratings tend to have smaller market capitalization, lower stock price, higher market sensitivity (beta), higher sensitivity to the size factor, lower dollar trading volume, lower liquidity, higher leverage, lower institutional ownership and higher uncertainty about future earnings.
- Credit rating downgrades do not cluster in bull or bear markets, or in recessions or expansions.
- The poor performance of distressed firms consistently surprises analysts, resulting in large negative earnings surprises and large negative forecast revisions.
- Stocks of firms with low credit ratings tend to be difficult to short (few shares available for borrowing) and illiquid, generally confounding exploitation of related anomalies.

In summary, *evidence indicates that many (but not all) well-known stock return anomalies derive* *their profitability from short positions in firms with low credit ratings during deteriorating credit conditions, with shorting constraints and illiquidity limiting exploitation.*

Originally published at http://www.cxoadvisory.com/5569/big-ideas/credit-ratings-and-stock-return-anomalies/ on April 23, 2010.

Amplifying Momentum with Volume and Accounting Indicators

April 19, 2010

Can investors enhance momentum returns for individual stocks with combination strategies that incorporate other technical and accounting indicators? In the April 2010 draft of their paper entitled "Technical, Fundamental, and Combined Information for Separating Winners from Losers", Cheng-Few Lee and Wei-Kang Shih investigate combined momentum strategies based on past stock returns, past trading volume and sets of fundamental (accounting) indicators. They consider two distinct sets of fundamentals: Piotroski's FSCORE for value stocks and Mohanram's GSCORE for growth stocks. Their combined strategy is long (short) past winners (losers) with weak (strong) past relationship between returns and trading volume and high (low) fundamental scores. Using stock return/volume and firm fundamentals data for a broad sample of NYSE and AMEX non-financial stocks spanning 1982-2007 (26 years), *they find that:*

At the end each month, the authors select the stocks in the top (bottom) quintile of book-to-market ratios as the value (growth) stock sample. They then perform further quintile sorts sequentially by past 12-month return, covariance of past return and past trading volume and FSCORE (GSCORE). The combined strategy exploits the extreme "good" and "bad" triple-sorted value and growth stocks over holding periods of one, three and six months after portfolio formation. A skip-month between sorting and hedge portfolio formation avoids short-term reversal (see "Short-term Reversal by Industry").

- The mean (median) book-to-market ratios for the value and growth samples are 2.24 (1.69) and 0.23 (0.18), respectively.
- The average monthly excess momentum-only returns (relative to three-month Treasury bill yield) for value (growth) stocks are 0.61% (0.91%), 0.58% (0.98%) and 0.49% (0.77%) over holding periods of one, three and six months, respectively.
- A strategy that combines momentum and return-volume covariance beats a momentum-only strategy for value stocks but not growth stocks. Specifically, a double-sort value stock strategy generates average monthly excess returns of 0.91%, 1.00% and 0.99% over holding periods of one, three and six months, respectively.
- A triple-sort strategy that combines momentum, return-volume covariance and FSCORE/GSCORE generates average monthly excess returns of:
    - 1.78%, 3.36% and 2.96% for value stocks using FSCORE over holding periods of one, three and six months, respectively.
    - 3.31%, 3.03% and 2.20% for growth stocks using GSCORE over holding periods of one, three and six months, respectively.
- Returns to a momentum-only strategy relate negatively to returns for the strategies based on FSCORE and GSCORE alone, suggesting volatility benefits from a combined strategy.

Note that this study does not address:

- The effects of reasonable trading frictions on net profitability of the strategies considered (which may face obstacles of high portfolio turnover and relatively low liquidity).
- The susceptibility of a complex rule (essentially multiple rules) to data snooping bias.
- The susceptibility of rules derived from past studies to second-hand data snooping bias passed from the parent studies.

In summary, *investors may be able to boost momentum returns for individual stocks substantially by incorporating information from past trading volume and detailed analysis of firm fundamentals.*

Originally published at http://www.cxoadvisory.com/5333/fundamental-valuation/amplifying-momentum-with-volume-and-accounting-indicators/ on April 19, 2010.

Reaction, Momentum and Reversion

April 6, 2010

A reader observed and asked: "There are two strategies, both of which appear to work, but which also seem contradictory to each other. Momentum says what goes up must go up further. Reversion says what goes up must come down. Both work? There must be something wrong here?!?

There is a stream of research that indicates three phases of price dynamics in equity markets, reaction – momentum – reversion, that operate over different horizons:

1. The reaction phase is short-term (roughly a month or less), wherein price tends to reverse recent momentum. "Short-term Reversal by Industry" examines this phase in detail.
2. The momentum phase is intermediate-term (roughly three months to a year), wherein price tends to continue its recent (multi-month) trend. Items in the Momentum Investing category cover this phase, and sometimes address the other two phases as well.
3. The reversion phase is long-term (roughly two to five years), wherein price tends to reverse a longstanding trend. Items in the Value Premium category address concepts of this phase but seldom assign any time frame to the process.

It is possible to combine the specifications for phase dynamics within a single portfolio. For example, one can impose a skip-month in momentum portfolios to avoid adverse reaction moves. And, one can choose stocks for which momentum is moving prices toward fair values rather than away from fair values (as noted in "What Works Best?").

Originally published at http://www.cxoadvisory.com/5063/value-premium/reaction-momentum-and-reversion/ on April 6, 2010.

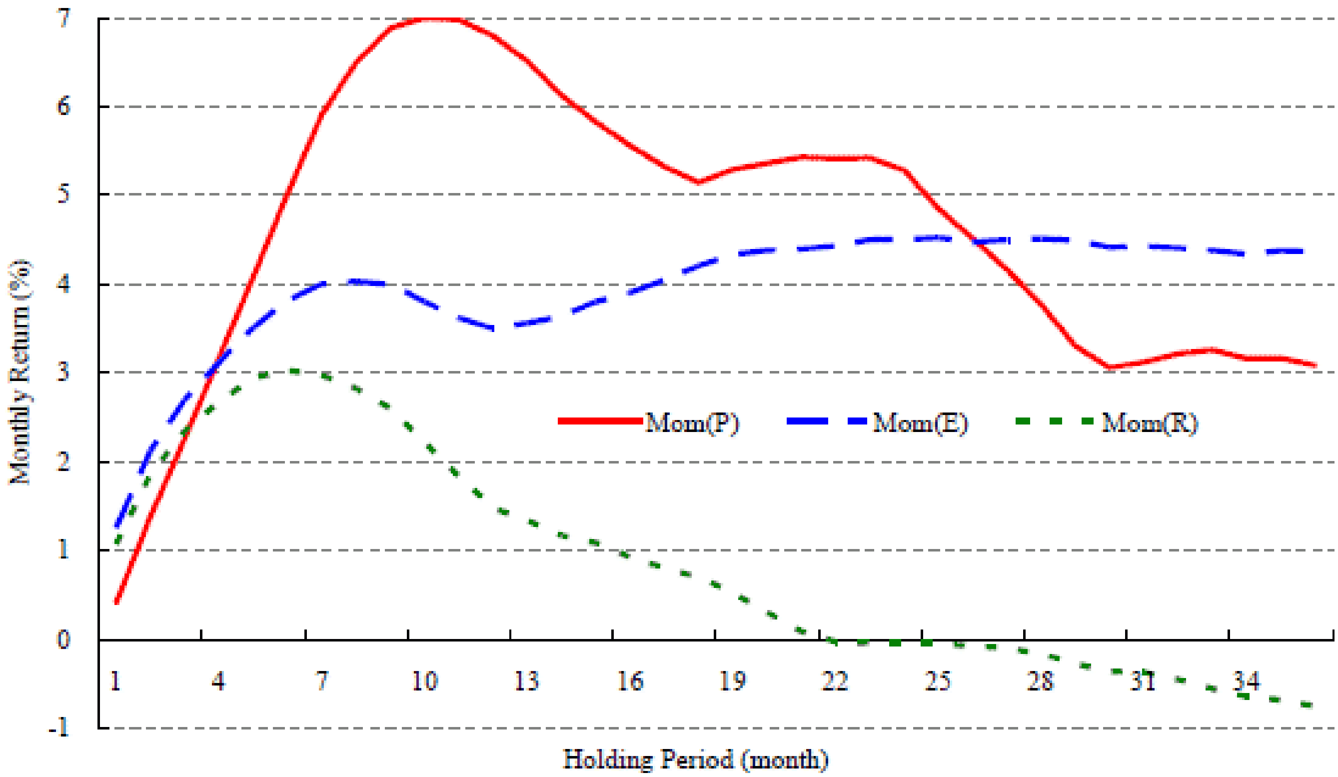
A Multi-momentum Potential

March 30, 2010

Are signals form firm earnings and revenue momentum additive to that from stock price momentum? In their March 2010 paper entitled "Price, Earnings, and Revenue Momentum Strategies", Hong-Yi Chen, Sheng-Syan Chen, Chin-Wen Hsin and Cheng-Few Lee examine the profitability and of a revenue momentum strategy, both standalone and in combination with price and earnings momentum strategies. They measure price momentum based on past stock returns, and earnings and revenue momentums with respect to historical earnings and revenues (not surprises relative to analyst forecasts). Using stock return, earnings and revenue data for a broad sample of U.S. stocks spanning 1974-2007, *they conclude that:*

- Returns for equally weighted hedge portfolios that are long (short) stock with high (low) momentum for each variable indicate that price/return momentum generates the largest average profit, followed by earnings momentum and revenue momentum. However, none of the three strategies is dominant. In other words, each variable separately offers investors meaningful information.
- Results for combination strategies indicate that investors evaluate these different momentums somewhat in concert, but not inefficiently.
  - Hedge portfolios formed from double sorts on average outperform single-sort portfolios, and one formed from a triple sort outperforms double-sort portfolios.
  - A particular triple-sort equally weighted hedge portfolio that is long (short) stocks with highest past returns, most positive earnings surprises and most positive revenue surprises (lowest past returns, most negative earnings surprises and most negative revenue surprises) generates an average monthly return of 1.57% over the sample period.
- Earnings momentum is more persistent than return momentum, while revenue momentum is relatively short-lived (see the chart below). Strong return and earnings momentum enhances the persistence of revenue momentum.
- Results suggest that investors do not immediately process the information conveyed by past returns, earnings surprises and revenue surprises,
  especially for extreme cases.

The following chart, taken from the paper, shows the average cumulative monthly returns for equally weighted hedge portfolios (high quintile minus low quintile) formed monthly over the entire sample period based on past return (P), earnings (E) and revenue (R) momentum separately and held for 36 months. Past return momentum profitability peaks for a holding period of about one year, while that for earnings momentum persists. Revenue momentum profitability is neither as strong nor as persistent as the other two strategies.



Note that the above results are exclusive of trading frictions, which would materially dent returns.

In summary, *evidence suggests that an investing strategy that combines past return, earnings and revenue momentums outperforms strategies based on only one or two of these momentums.*

Originally published at http://www.cxoadvisory.com/2470/momentum-investing/a-multi-momentum-potential/ on March 30, 2010.

Are Momentum Strategies Fragile?

March 21, 2010

A reader commented and asked: “I am interested in Mebane Faber’s 10-month SMA timing strategy, as it seems to match the market with less risk and outperform other moving average strategies I’ve seen. Based on the results of ‘Is There a Best SMA Calculation Interval for Long-term Crossing Signals?’, it seems that Faber’s strategy is not brittle as far as choosing an 8-, 10-, 12- or 14-month SMA. However, what if I were to trade on a day other than the end of the month? Would I get drastically different results? If so, that might suggest that Faber’s choice of day is ‘data mining’ and the performance of his strategy may not persist.”

While not precisely addressing your question, the following points are perhaps close enough in concept to address the concern.

The momentum investing approach, whether implemented via simple moving average (SMA) crossovers or lagged returns (or a combination) may be fragile with respect to exact parameter selection:

1. The second chart and associated discussion of 200-day SMA crossovers in “The *TimingCube* Market Timing Advisory Service” finds that results for a 200-day SMA crossover strategy are sensitive to anticipating the crossover (trading at the same close as the crossover). Waiting a day after crossover substantially reduces crossover strategy returns.
2. As found in “Simple Sector ETF Momentum Strategy Robustness/Sensitivity Tests”, there is substantial variation in outcomes with the momentum ranking interval, making the six-month and ten-month ranking intervals look lucky.
3. A reader reported in response to this second analysis his own findings that shifting the momentum ranking interval off the end of the month (for a six-month ranking interval) affects returns substantially, making the end of the month appear lucky. This kind of testing is very time-consuming and may involve some judgments about what constitutes a month.

Possible explanations for such fragilities include:

- The specific strategy parameter values are lucky, and luck will not persist outside the test sample.
- Many investors have adopted and are acting on these parameter values, and results may persist as long as investors continue to act synchronously.

- The sample periods in the tests are too short (or the underlying distributions are too intractable) for reliable inference.

It seems plausible that the end-of-the-month choice for momentum ranking and the anticipatory execution of 200-day SMA crossover signals are “natural selections” rather than data snooping artifacts. The reason for choice of momentum ranking interval length seems more arguable.

Mal Williams reported results for a sensitivity test of his momentum-based asset class rotation strategy (see “An Investor’s Asset Class Momentum Trading Strategy”). He tested trading 1, 15, 30 and 60 days after the initial signal (requiring that the asset still be on the buy list after the delay) — the longer the delay, the lower the overall portfolio return over a 20-year period. While total return is higher for trading right away, so is volatility (but risk-adjusted return is still higher). “Perhaps the magic is being early in responding to a signal.”

Originally published at http://www.cxoadvisory.com/3160/momentum-investing/are-momentum-strategies-fragile/ on March 21, 2010.

Short-term Reversal by Industry

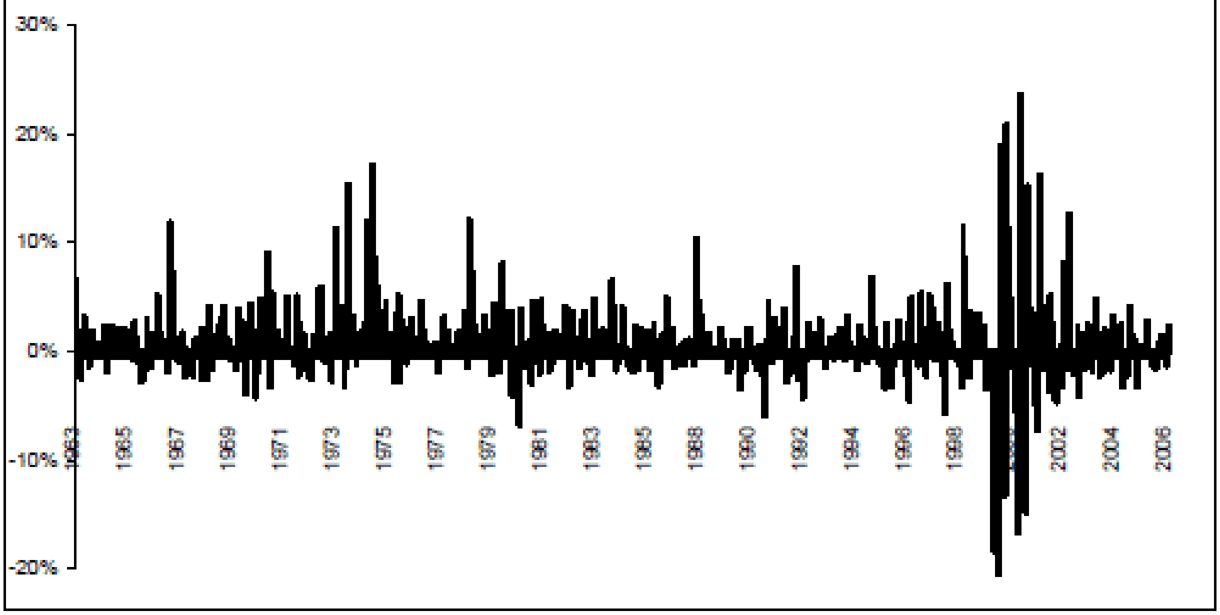
March 18, 2010

Various studies find that returns on individual stocks exhibit tendencies for short-term (one month) reversal, medium-term (3-12 months) momentum and long-term (2-5 years) reversal. The short-term reversal is the basis for the skip-month included in some medium-term momentum strategies. Is there a way to concentrate the short-term reversal? In the March 2010 update of their draft paper entitled "Industries and Stock Return Reversals", Allaudeen Hameed, Joshua Huang and Mujtaba Mian examine monthly return reversal using stocks grouped into 24 industries, reasoning that such groups share common sources of return correlations. Using return, industry and characteristics data for a broad sample of NYSE/AMEX stocks spanning 1963-2006, *they conclude that:*

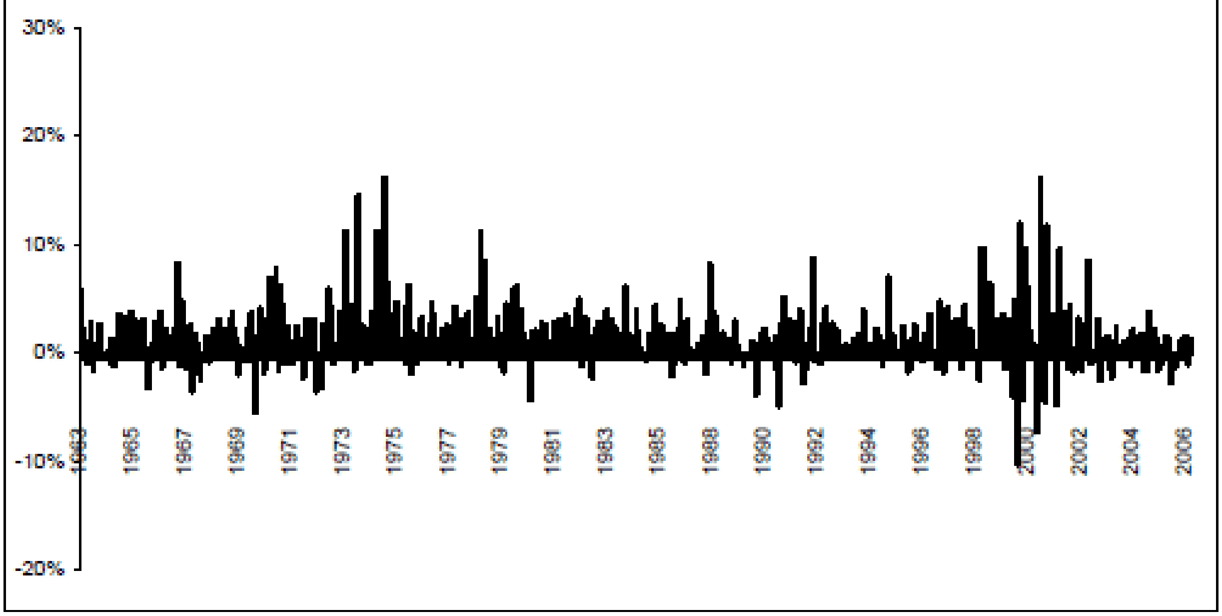
- A hedge strategy that is long (short) the equally weighted fifth of stocks that are the biggest losers (winners) the prior month within each of the 24 industries, reformed monthly and weighting industries equally, generates an average monthly return of 1.46%. A comparable portfolio executed across the total sample of stocks generates an average monthly return of only 1.05%. The standard deviation of monthly reversal returns is 2.9% (4.1%) for the intra-industry (total sample) strategy. (See the charts below.)
  - Semiconductors & Semiconductor Equipment (Software & Services) have the largest (smallest) intra-industry average monthly reversal of 3.1% (0.79%).
  - Intra-industry reversals are stronger for illiquid, small and highly volatile stocks, suggesting that liquidity risk is an important source of short-run reversals.
  - Skipping a week between the one-month formation and holding periods eliminates the the short-term reversal effect for the total sample of stocks, but not for industry groups.
- Stocks that outperform or underperform the total sample but not their industries tend to exhibit momentum rather than reversal. A hedge strategy that capitalizes on both this inter-industry momentum and intra-industry reversals produces a raw (risk-adjusted) average monthly return of 2.3% (2.0%). This strategy produces positive returns for 77% of sample months.

The following charts, taken from the paper, compare month-by-month returns for hedge strategies that are long (short) the equally weighted fifth of stocks that are the biggest losers (winners) the prior month, reformed monthly. The top chart shows returns for this strategy applied across the total sample of stocks (unconditional), while the second shows returns for the strategy applied separately to 24 equally-weighted industries (industry sorted). The third chart shows the differences between the latter and former monthly returns. Results indicate that: (1) reversal returns are persistent over time; (2) intra-industry reversal returns are less volatile than total sample reversal returns; and, (3) intra-industry reversal returns tend to be larger than total market reversal returns.

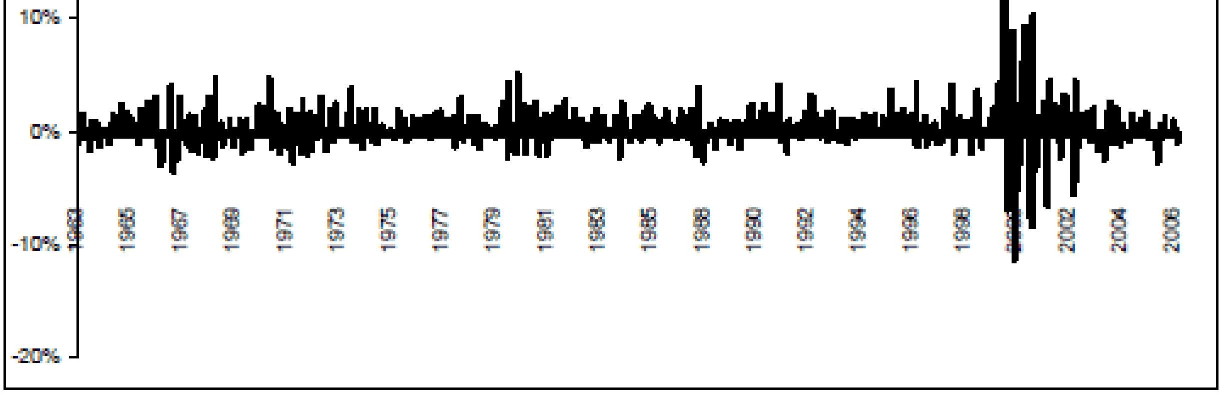
Unconditional Monthly Returns of Losers - Winners



Industry Sorted Monthly Returns of Losers - Winners



Excess Monthly Returns from the Industry Sorted Strategy
Relative to the Unconditional Startgey



Return estimates apparently do not account for any trading frictions, which could be substantial.

In summary, *evidence suggests that investors can concentrate the short-term (one month) stock return reversal effect by focusing at the industry level.*

The role of liquidity risk and the inter-industry momentum effect described above imply that short-term reversal may not be evident in broad, value-weighted market indexes.

Originally published at http://www.cxoadvisory.com/2445/momentum-investing/short-term-reversal-by-industry/ on March 18, 2010.

Amplifying Momentum Returns with Idiosyncratic Volatility

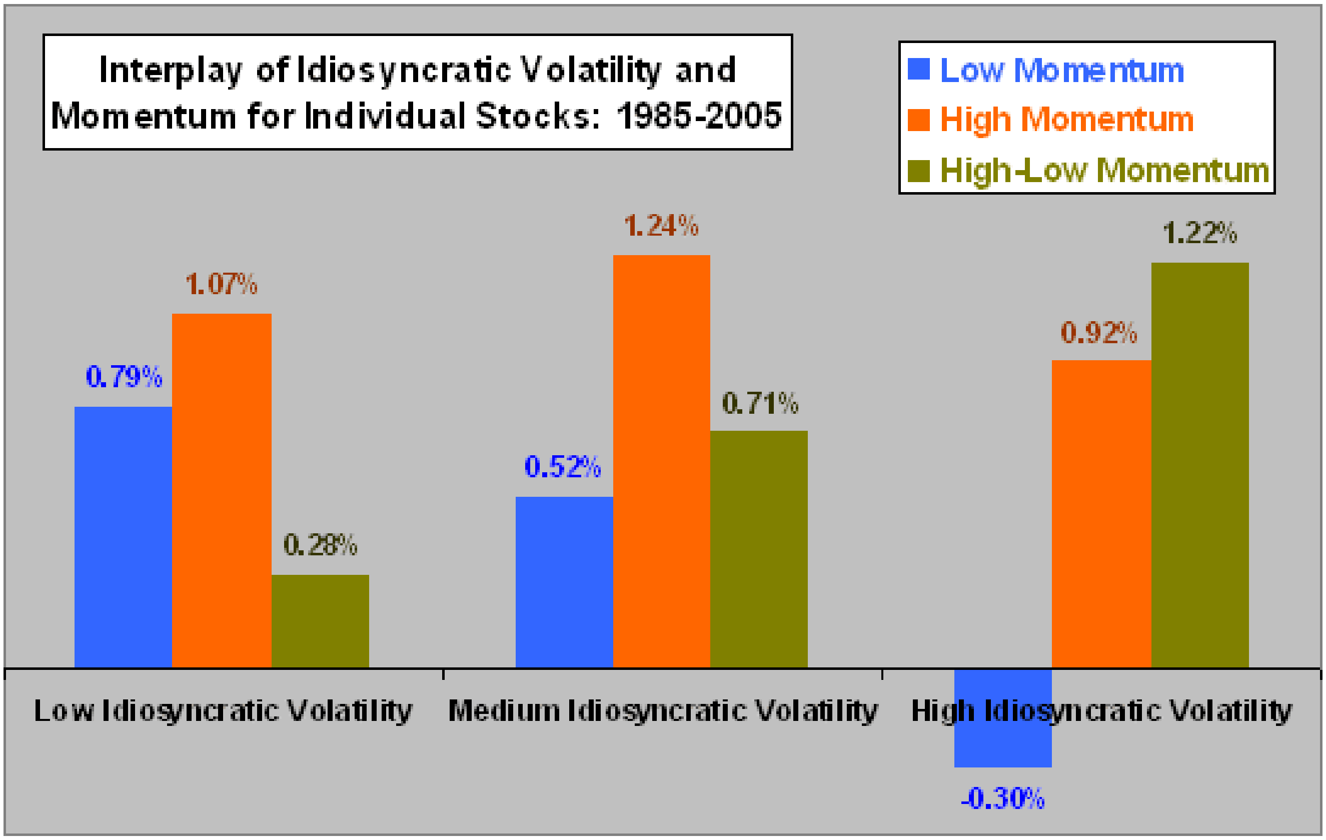
March 5, 2010

Does positive feedback trading, indicated by an adjusted measure of return autocorrelation, enhance momentum profitability? In the February 2010 version of their paper entitled "Positive Feedback Trading Activities and Momentum Profits" [apparently removed from SSRN, thus casting doubt on its credibility], Thomas Chiang, Xiaoli Liang and Jian Shi examine the relationship between positive feedback trading and profitability of momentum strategies. The momentum parameters for their investigation are a six-month ranking interval followed by a six-month holding interval. Measurement of positive feedback trading is for a six-month window coinciding with the momentum ranking interval. Using daily stock return data for a broad sample of U.S. stocks spanning 1985-2005, *they conclude that:*

- Stocks that exhibit positive feedback trading generate much higher average momentum profits than stocks that do not (although profits are still substantial for stocks without positive feedback trading).
- Stocks exhibiting past positive feedback trading are much more likely to be extreme losers than extreme winners, perhaps due to stop losses and portfolio insurance policies. Amplification of momentum returns from positive feedback trading therefore derives largely from shorting losers.
- However, stocks in extreme winner momentum portfolios exhibit the highest concentration of positive feedback trading six months later.
- Both positive feedback trading and momentum profitability increase with market volatility and idiosyncratic volatility, with idiosyncratic volatility dominating. Controlling for idiosyncratic volatility, the difference in momentum profitability between stocks that do and do not exhibit positive feedback trading nearly disappears. In other words, idiosyncratic volatility is a good proxy for the level of positive feedback trading (see the chart below).
- Positive feedback trading relates positively to firm credit risk and negatively to firm size.

The following chart, constructed from data in the paper, compares average monthly momentum returns over six-month holding periods for different levels of idiosyncratic volatility. An initial sort ranks stocks into three groups by idiosyncratic volatility (stock volatility minus beta-adjusted market volatility) over the past six months. A second sort ranks each idiosyncratic volatility group by momentum (cumulative return over the same six months). Average monthly returns are for a six-month holding period that immediately follows the six-month ranking period.

Results show that a hedge portfolio that is long (short) past momentum winners (losers) performs best within the third of stocks exhibiting the highest idiosyncratic volatility. Results suggest that there may be both fundamental (earnings growth persistence) and behavioral (reaction to returns) components to this amplified momentum return.



In summary, *evidence suggests that investors may be able to enhance exploitation of <u>downside</u> momentum by focusing on stocks with high idiosyncratic (non-beta) volatility.*

Originally published at http://www.cxoadvisory.com/2425/volatility-effects/amplifying-momentum-returns-with-idiosyncratic-volatility/ on March 5, 2010.

Lussenheide's Basic Timing Strategy

February 17, 2010

A reader asked whether Lussenheide Capital Management's momentum timing mechanism (100-day NASDAQ Composite Index moving average crossings, with proprietary filter) beats buy and hold over the long run, noting that the company's web site presents at "Trend Following Performance" an independently validated annualized return of over 16% for "a very simple trend following system." The discussion of performance states: "The systems used here at… Lussenheide Capital Management Inc., uses [sic] this basic system, along with a mechanical, proprietary trading filter. Although our returns are comparable or better with those shown below, our system has more desirable characteristics, including fewer trades and less whipsaws amongst others." The notes at the bottom of the performance table state that results exclude "fund expenses" and "advisory management fees." Without the specifications for the proprietary filter, we can test only basic concepts directly. Using daily closes of the NASDAQ Composite Index and daily dividend-adjusted closes for various potential trading vehicles through 2/12/10, *we find that:*

Based on data since fund inception, we test the performance of a 100-day simple moving average (SMA) trading signal for the following diversified exchange-traded funds (ETF) and mutual funds:

- S&P Depository Receipts (SPY) since 1/29/93.
- Rydex NASDAQ-100 (RYOCX) since 6/17/94.
- Rydex Nova (RYNVX) since 6/17/94.
- PowerShares QQQ (QQQQ) since 3/10/99.
- Fidelity NASDAQ Composite Index Tracking (ONEQ) since 10/1/03

Sample periods therefore range from about 6.5 years 16 years, small compared to a 100-day SMA.

Trading assumptions are as follows:

- When the NASDAQ Composite Index crosses above (below) its 100 trading-day SMA, buy (sell) a specified fund. Trades occur at the close coincident with signal generation (we slightly anticipate the signal).
- Return on cash is the contemporaneous short-term Interest Rate Composite.
- Trading frictions (transaction fee plus bid-ask spread) for ETFs are a small percentage of portfolio value (a range of 0.00% to 0.25%). Trading frictions for the Rydex funds are zero (or rather, impounded in fund performance).
- There is an annual management fee of 1.8%, deducted the last trading day of each

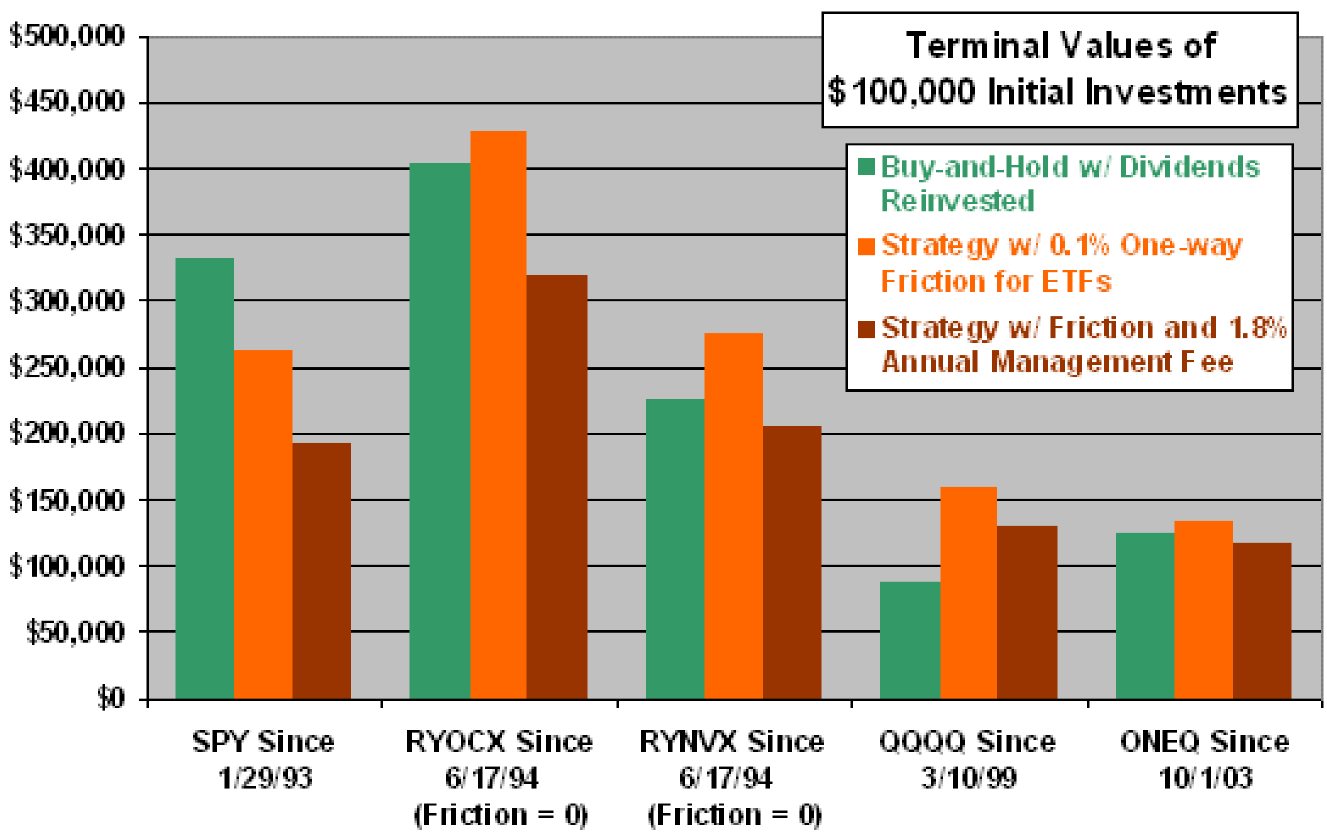
calendar year.

- Ignore tax implications of trading.

The following chart shows the terminal values of $100,000 initial investments in each of the five trading funds/timeframes for: (1) a buy-and-hold strategy; (2) the 100-day SMA crossing strategy with with 0.1% one-way trading friction for the ETFs; and, (3) the 100-day SMA crossing strategy with with 0.1% one-way trading friction for the ETFs and 1.8% annual management fee for all funds. Results show that:

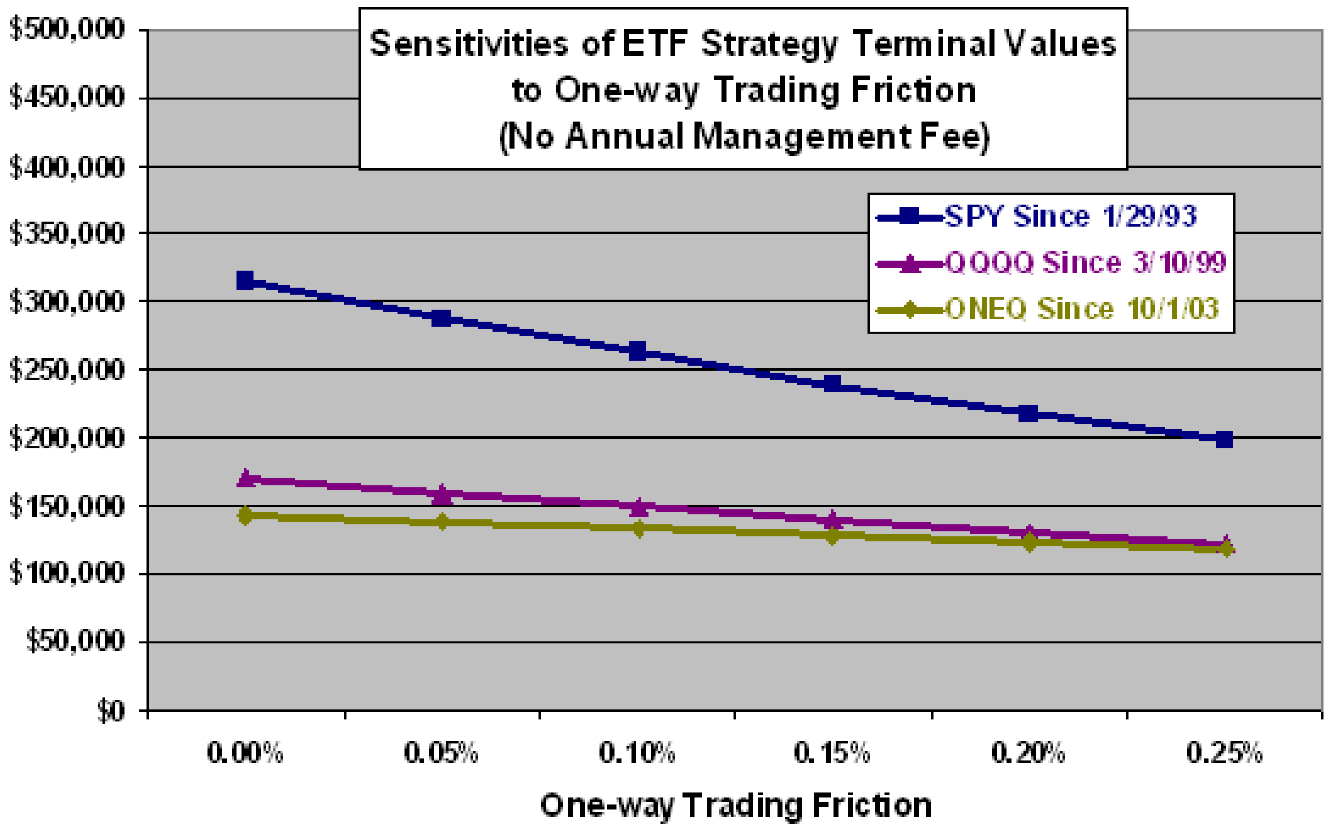
- With trading friction but no management fee, the 100-day SMA crossing strategy beats buy-and-hold in four of five cases.
- With trading friction and management fee, the 100-day SMA crossing strategy beats buy-and-hold in one of five cases.
- The timeframe of analysis may be decisive, with performance of the timing strategy materially dependent on broad market trend and volatility during the test period (see the blog entry of 2/8/10).

How sensitive are results to the assumed level of trading friction?

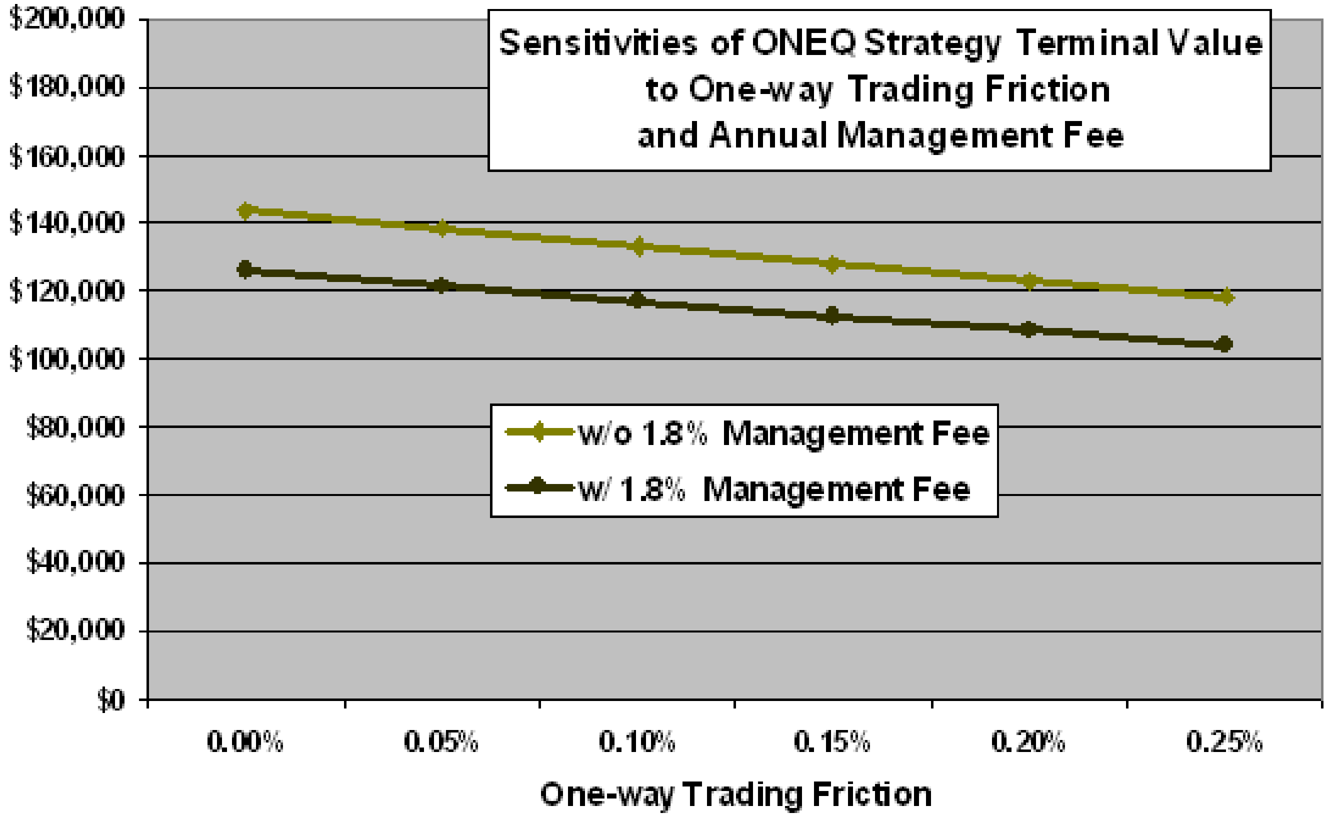


The next chart shows the terminal values of $100,000 initial investments in each of the three ETFs/timeframes for one-way trading frictions ranging from 0.00% to 0.25%. The cumulative effect of trading friction over long periods can be substantial, and sometimes decisive with respect to outperforming a buy-and-hold benchmark. Actual trading frictions depend on specific broker transaction fees, trading vehicle bid-ask spread and portfolio size. Achieving low trading friction is especially problematic for small portfolios.

How big is the effect of a management fee?



The final chart shows the terminal values of $100,000 initial investments in ONEQ since 10/1/03 for one-way trading frictions ranging from 0.00% to 0.25%, with and without the annual management fee. The cumulative effect of the management fee is substantial.



For reference, the following table lists the daily average (arithmetic mean) returns and standard deviations of daily returns for the five funds/timeframes. The "Buy-and-Hold" column involves no trading. The "Strategy Gross" column incorporates market timing based on 100-day SMA crossings as described above. The "Strategy w/ Friction" column debits "Strategy Gross" with 0.1% one-way trading friction (except for the Rydex funds). The "Strategy w/ Friction and Fee" column debits "Strategy w/ Friction" with a 1.8% management fee charged the last trading day of each calendar year. In general, the 100-day SMA trading strategy reduces average daily return, but also reduces daily return volatility.

		Buy-and-Hold	Strategy Gross	Strategy w/ Friction	Strategy w/ Friction and Fee
SPY Since 1/29/93	Average Daily Return	0.036%	0.030%	0.025%	0.018%
	Standard Deviation of Daily Returns	1.25%	0.74%	0.74%	0.76%
RYOCX Since 6/17/94	Average Daily Return	0.057%	0.044%	0.044%	0.037%
	Standard Deviation of Daily Returns	2.07%	1.24%	1.24%	1.25%
RYNVX Since 6/17/94	Average Daily Return	0.039%	0.032%	0.032%	0.025%
	Standard Deviation of Daily Returns	1.91%	1.12%	1.12%	1.13%
QQQQ Since 3/10/99	Average Daily Return	0.019%	0.027%	0.022%	0.015%
	Standard Deviation of Daily Returns	2.16%	1.20%	1.20%	1.21%
ONEQ Since 10/1/03	Average Daily Return	0.023%	0.026%	0.021%	0.013%
	Standard Deviation of Daily Returns	1.41%	0.81%	0.81%	0.82%

Note that evidence from simple tests:

- Does not reliably point to any “best” SMA calculation interval for generating crossing signals to exploit long-term stock market trends over the time frames tested above.
- Does not show that buffering SMA crossing signals to reduce trading enhances performance.

The Disclosure for Lussenheide Capital Management’s web site states:

- “No representation is being made that the information will produce trading profits.”
- “In no event shall Bill Lussenheide or his family be held liable for any special, incidental, or consequential damages, whatsoever (including: without limitation, trading losses or any other losses incurred) arising from the use or inability to use the information contained in his publications…”

In summary, *evidence from simple tests on limited samples supports a belief that a strategy employing long-term simple moving average crossing signals to enter and exit equities may outperform a buy-and-hold strategy, depending on market conditions and the level of trading frictions/fees.*

Originally published at http://www.cxoadvisory.com/2830/technical-trading/lussenheides-basic-timing-strategy/ on February 17, 2010.

Momentum vs. Value

February 12, 2010

A reader asked: "Have you done any backtesting to compare value investing versus market timing? Magic Formula Investing seems to rank #1 in value investing and Decision Moose seems to stand out for market timing. Is there any direct comparison between Magic Formula Investing vs. Decision Moose?"

It is arguable that both momentum investing (trend-following, such as Decision Moose) and value investing (valuation-implied mispricing, such as Magic Formula Investing) are timing approaches at different horizons. The former expects intermediate-term reward (months) from trend continuation, and the latter expects long-term reward (years) from trend reversion. It is also arguable that they are complementary consequences of the same market behavior. See "What Works Best?" for some discussion and research citations. Because of their different horizons, it should be feasible to combine value and momentum in an investing strategy for some enhancement/hedging benefits, as indicated by a couple of the citations.

For exploration of the momentum and value together, see especially:

> "Combining Value and Momentum Across Asset Classes"
>
> "Four Factors and Two Regimes"
>
> "Combined Value-Momentum Tactical Asset Class Allocation"

Note that Decision Moose operates at the asset class (fund) level, and Magic Formula Investing operates at the stock level. This difference may make them unsuitable for a pure investigation of momentum versus value. A pure investigation would require a very long sample period and a very large sample of assets (stocks). Handling of trading frictions would be complex, and outcomes would probably be very sensitive to trading friction assumptions. Parameter settings used to define high-momentum and high-value stocks may seem arbitrary. Assessing any difference in the level of data snooping bias between the competing approaches would be problematic.

Originally published at http://www.cxoadvisory.com/3121/fundamental-valuation/momentum-vs-value/ on February 12, 2010.

Any Thoughts on “The Capitalism Distribution?”

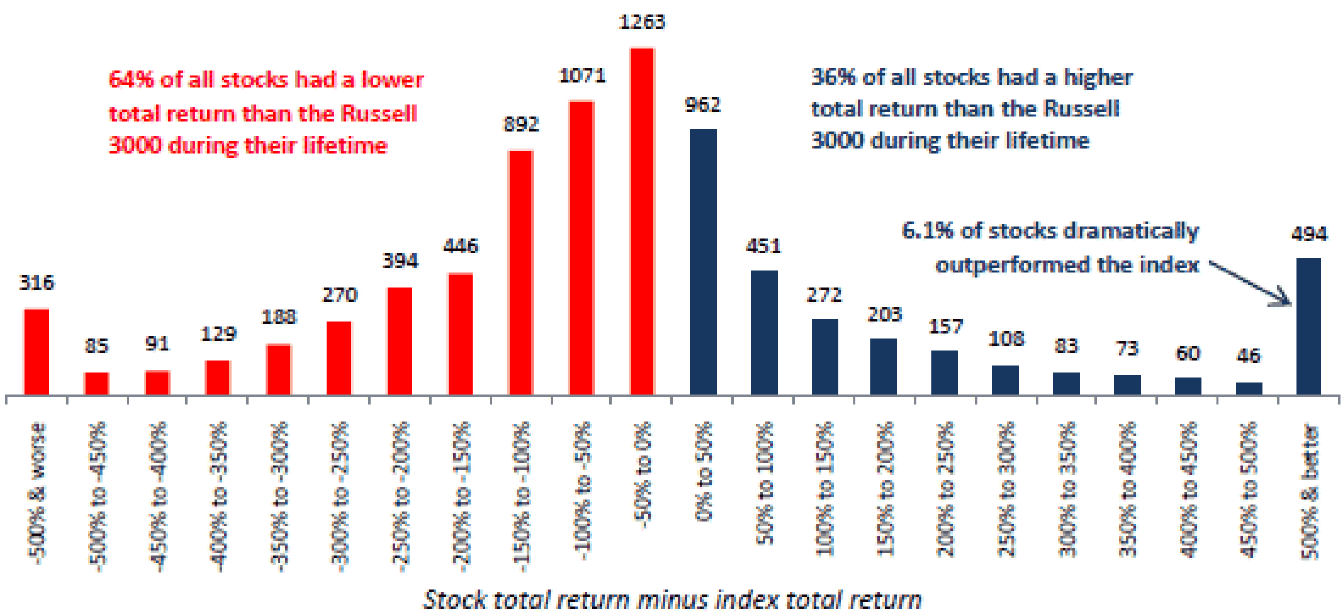
December 26, 2009

A reader asked: “If you have some thoughts on the claims in the article ‘The Capitalism Distribution’ by Blackstar Funds, LLC, I would be most interested in hearing them.”

“The Capitalism Distribution” examines returns for about 8,000 “stocks that would have qualified for membership in the Russell 3000 Index at some point in their lifetime” over the period 1983-2006, finding that (with dividends reinvested):

- 39% of these stocks were unprofitable.
- 18.5% lost at least 75% of their value.
- 64% underperformed the capitalization-weighted Russell 3000 Index (see the chart below). “…market capitalization weighted indexation is like a simple trend-following system that rewards success and punishes failure.”
- 25% accounted for all of the Russell 3000 Index gains.

The following chart, taken from the paper, shows the distribution of total returns for individual stocks during their lifetimes relative to the return for the Russell 3000 Index over the same intervals during 1983-2006.



The principal conclusion of the paper is: “…the biggest winners on annualized return and total return basis tended to have one thing in common while they were accumulating market beating gains. Relative to average stocks they spent a disproportionate amount of time making new multi-year highs… Stocks that generate thousands of percent returns will typically hit new highs hundreds of times, usually over the course of many years. Could it be this simple; long term trend following on stocks?”

Some observations:

- Their principal conclusion seems tautological. The leap from past multi-year highs to future performance is not obvious. The findings in the final table of the paper regarding stock performance “On the way up” and “After the peak” are ex post. One needs ex ante analysis to assess exploitability (such as “Mutual Fund Momentum Measure Fly-off”, “Trading After 52-week Highs and Lows”, “Trading After N-day Highs and Lows” and “The 52-Week High as a Momentum Indicator for Individual Stocks”).
- How realistic and pivotal is the assumption of dividend reinvestment for long-run returns of both indexes and a broad sample of individual stocks? (See the first bullet in “One Up on the Fed Model?”.) In other words, if investors took dividends as cash instead of more stock, how would the distribution of returns change? Might some investors hold low performers to collect high cash dividends? For such a macro study, the broad reinvestment assumption might overstate the performances of indexes and winners and understate the performances of losers over the long run.
- What is the effect of comparing stock performances over different intervals within the overall sample period? As the authors note, the shorter average lifetime of losers compared to winners potentially distorts aggregate results by cycling losers through the sample faster than winners.
- Would results be different for periods other than 1983-2006?

Blackstar Funds, LLC has a follow-up paper on exploiting stock long-term price highs entitled “Does Trend Following Work on Stocks?”. In this analysis, the authors base position entry on “all-time highest close” and position exit on “average true range trailing stops.” They apply round-trip trading friction of 0.5% (arguably low for individuals attempting to hold a diversified portfolio), with results as follows:

- Win rate is 49.3%.
- Ratio of average winning trade return to average losing trade return is 2.56.
- Weighted average of the trade results distribution is about 15.2%, with average holding period 305 calendar days.
- Portfolio-level analysis over 1991-2008 generates an annualized return of 15.5% with standard deviation of annual returns 15.6% and maximum drawdown -29.3% (compared to 7.9% / 14.3% / -44.9% for the S&P 500 Index).

Both papers are empirical, not addressing either behavioral or risk-based momentum theory.

Originally published at http://www.cxoadvisory.com/3100/momentum-investing/any-thoughts-on-the-capitalism-distribution/ on December 26, 2009.

TimingCube Market Timing Advisory Service

December 18, 2009

A reader requested a review of the *TimingCube* market timing advisory service, which relies "on the Trend Timing Model to detect major trend changes in the broad market and to issue clear, definitive Buy and Sell signals, on average three to five times per year." The offeror provides a history of "all 'live' *TimingCube* signals since June 18, 2001." Using this record of 36 signals, daily S&P Depository Receipts (SPY) closes adjusted for dividends over the period 6/17/01 through 12/16/09 and daily closes of the S&P 500 Index over the period 8/30/00 through 12/16/09, *we find that:*

The following chart compares the gross returns from trading SPY based on the 36 live *TimingCube* signals to those for buying and holding SPY during the same intervals. Calculations assume implementation of each *TimingCube* signal at the close on the day after issuance. *TimingCube* returns do not include trading frictions or costs of carrying short positions.

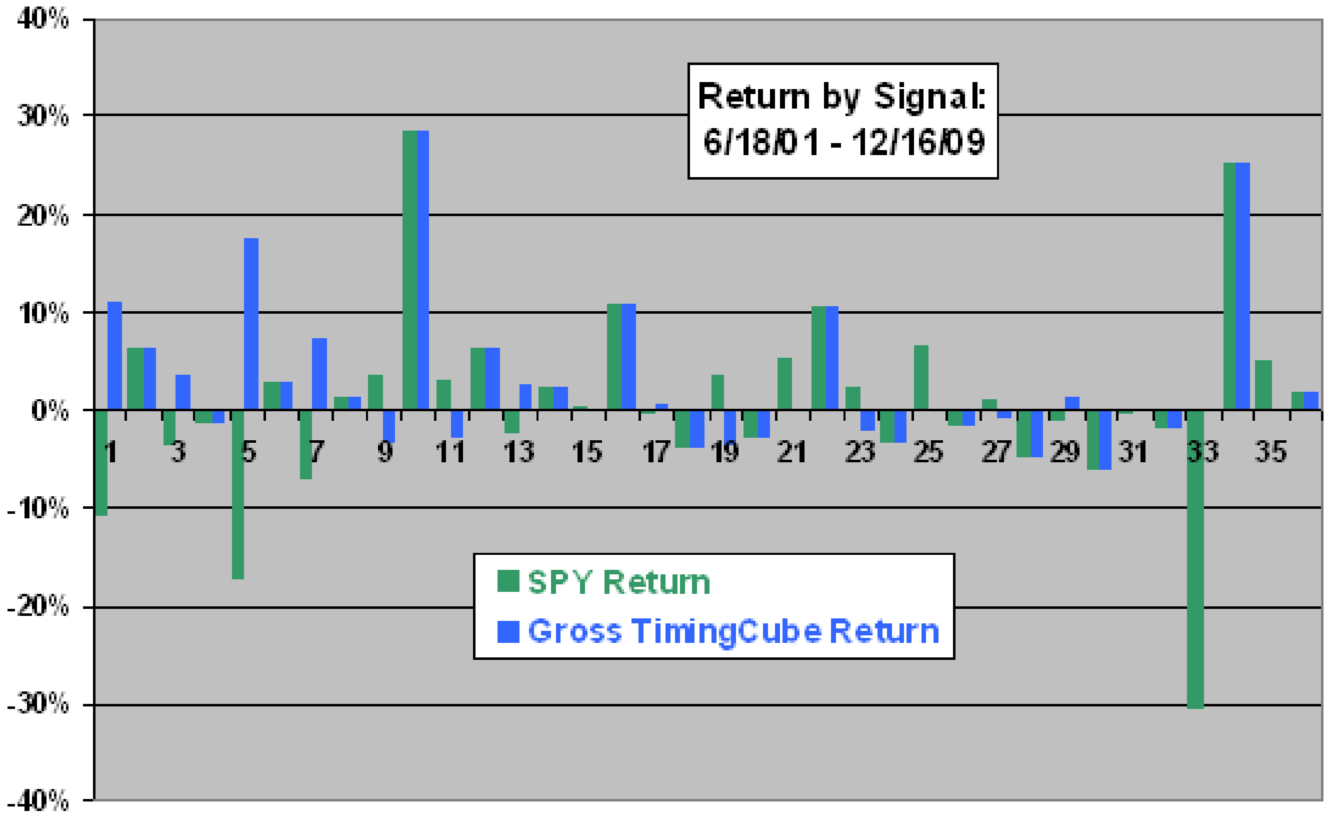
Over the sample period, the *TimingCube* signals successfully reverse or avoid the most dramatic SPY losses but otherwise are not dramatically different from buying and holding SPY. Some metrics of note:

- Overall, the average gross return per signal based on *TimingCube* signals (buy-and-hold) is 2.7% (0.7%).
- During bullish market conditions, the average gross return per signal based on *TimingCube* signals (buy-and-hold) is 3.0% (3.7%).
- During bearish market conditions, the average gross return per signal based on *TimingCube* signals (buy-and-hold) is 2.3% (-5.8%).

In general, it appears that the *TimingCube* signals substantially boost (modestly depress) returns during bearish (bullish) market conditions. It is therefore favorable to *TimingCube* to start the sample period during bear market conditions.

Using opening prices for *TimingCube* transactions (since signals are available after the prior close but before the open) might affect returns slightly. Applying trading frictions and shorting costs would reduce *TimingCube* returns, depending on account size and specific broker fees.

Do these results mean that *TimingCube* is worth its price?



The next chart compares average daily returns during 6/18/01 through 12/16/09 for timing of SPY based on *TimingCube* signals and three simple (and free) alternatives:

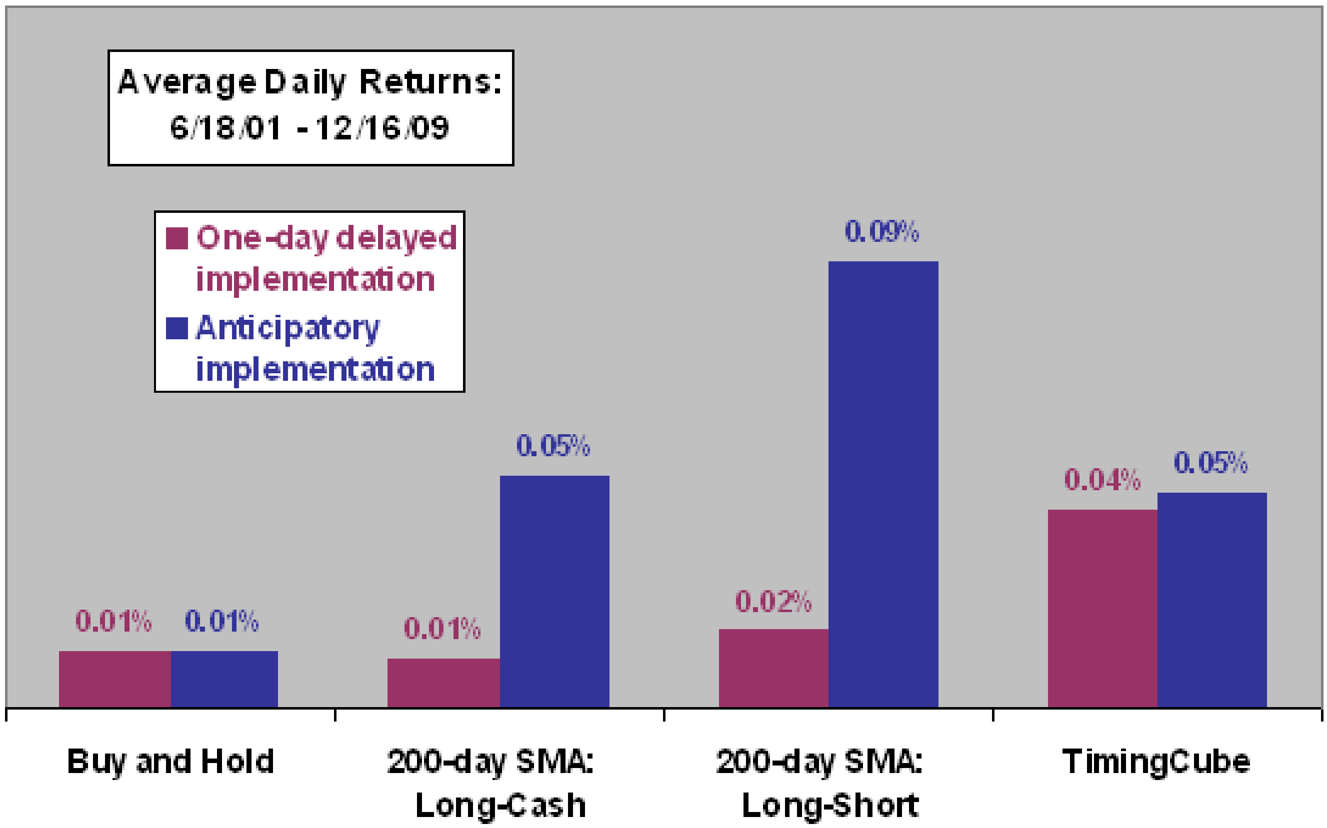
1. Buy and hold SPY.
2. Go long SPY (to cash) when the S&P 500 Index crosses above (below) its 200-day simple moving average (200-day SMA: Long-Cash).
3. Go long (short) SPY when the S&P 500 Index crosses above (below) its 200-day SMA (200-day SMA: Long-Short).

Alternatives 2 and 3 each generate 72 trading signals over the sample period. Since the signals derive from market closes, we first implement each alternative at the following market close (one-day delayed implementation). Because the use of 200-day SMA crossovers by many investors may move the market, we also test a variation with crossovers anticipated just before the close and implemented at the same close (anticipatory implementation). For comparison, we test similar prior-close anticipation of *TimingCube* signals.

For each change in position for 200-day SMA signals and TimingCube signals, we assume a rough trading friction of 0.25%. We do not account for costs of holding short positions, which represent 44% of trading days for alternative 3 above and 28% of trading days for *TimingCube* signals.

Results suggest that a nimble investor may be able to out-time *TimingCube* by closely monitoring and “front-running” S&P 500 Index closing 200-day SMA crossovers. However, results also suggest that returns for 200-day SMA crossover signals are fragile with respect to exact implementation date, while *TimingCube* signals are not.

Incorporation of shorting costs would reduce 200-day SMA: Long-Short returns and *TimingCube* returns, the former more than the latter. More precise assumptions on trading frictions would favor 200-day SMA: Long-Cash over both 200-day SMA Long-Short and *TimingCube*, and *TimingCube* over 200-day SMA: Long-Short.



The above analyses assume that the live *TimingCube* trade signal data is accurate and complete as presented. The sample of signals is fairly small for the types of analyses used, especially given the dependence of *TimingCube* outperformance on the relative frequency of bull and bear market conditions.

The *TimingCube* disclaimer states:

> "*TimingCube* does not guarantee or warrant the quality, accuracy, completeness, timeliness, appropriateness or suitability of the Information or of any product or services referenced on the Site. *TimingCube* assumes no obligation to update the Information or advise on further developments concerning topics mentioned. … *TimingCube* IS PROVIDING THIS SITE AND THE INFORMATION ON AN "AS IS" BASIS AND MAKES NO REPRESENTATIONS OR WARRANTIES OF ANY KIND WHATSOEVER WITH RESPECT TO THE SITE OR THE INFORMATION OR WITH RESPECT TO THE USE OR SUITABILITY OF THE SITE OR THE INFORMATION FOR ANY PURPOSE. …*TimingCube* disclaims all warranties, representations and conditions regarding the Site and the Information, including, without limiting the generality of the foregoing, all implied warranties and conditions of merchantability, fitness for a particular purpose…"

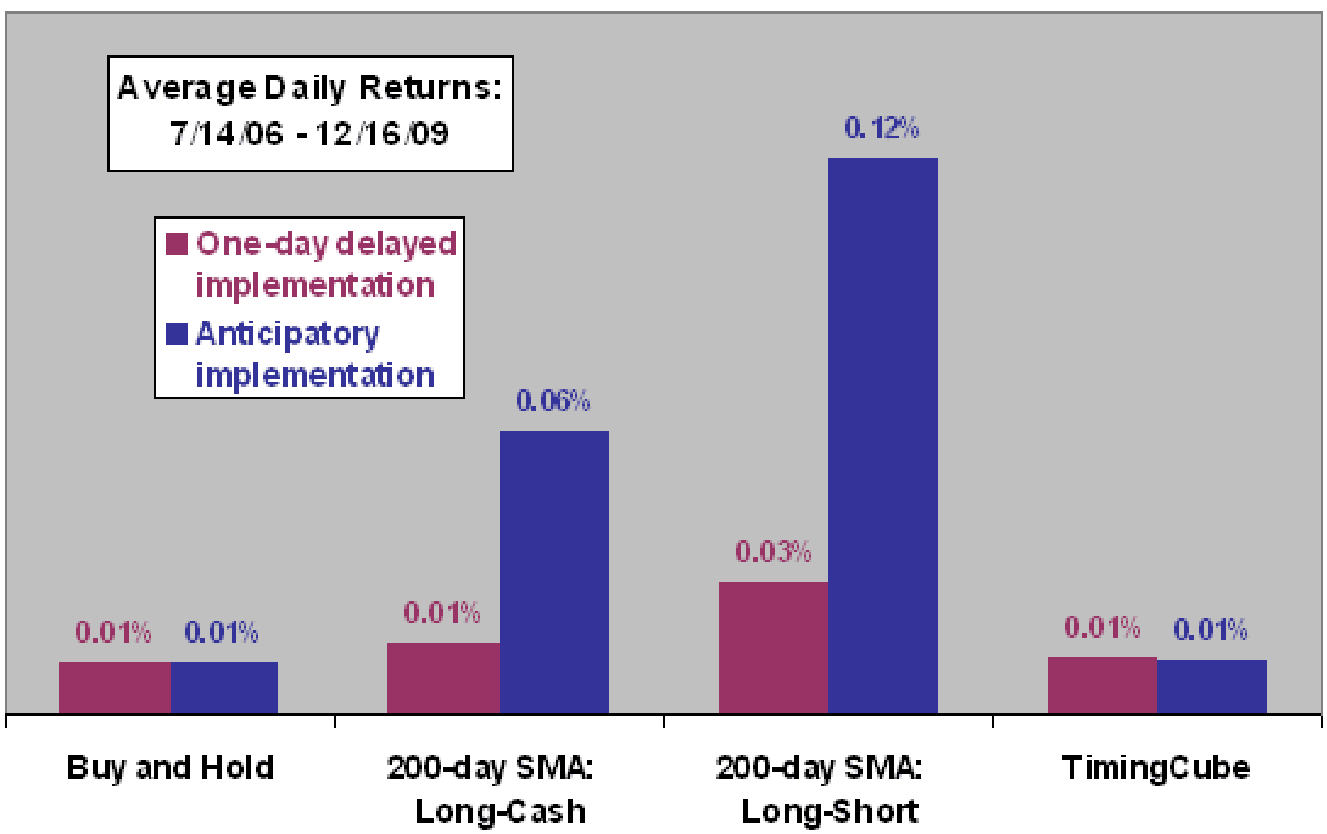
In summary, *evidence from simple tests indicates that the* TimingCube *market timing advisory service may outperform a buy-and-hold strategy over periods that include bear market conditions, but that nimble use of 200-day simple moving average crossover signals may do as well or better than* TimingCube *signals.*

See Guru Grades for links to evaluations of the commentaries and advice of other investing experts.

Reader Michael Stokes of the MarketSci Blog noted in an email that *TimingCube* implemented a revision to their timing model in July 2006. *TimingCube* states that the "current timing Model… went into effect on July 14, 2006." How has *TimingCube's* model done since that revision?

The following chart repeats the SPY-based analysis used to generate the second chart above for the subperiod 7/14/06 through 12/16/09. Results based on average daily returns show that *TimingCube* has not outperformed a buy-and-hold strategy and has likely underperformed 200-day SMA crossover signals during this subperiod, despite avoiding the steep drop in the market from late 2008 through early 2009.

However, *TimingCube* has a standard deviation of daily returns for this subperiod of 0.94%, compared to 1.77% for buy-and-hold. The 200-day SMA: Long-Cash has an even lower 0.64% standard deviation of daily returns.



Another reader commented: “I subscribed to *TimingCube* for a couple of years. They changed the system more than once and then hid their actual results. Also, the web site was not even created until 10/31/01, so signals before then are bogus. When their system went south, they started new services. When those went south, they changed those as well. I think *MarketWatch* did a piece on them. Not good results.”

> Your recollection of *TimingCube* service changes may be correct, but the articles discovered via a search of “TimingCube” at *MarketWatch* are favorable:
>
> > “Crash of 2008 Survivor is Bullish”: “Over the past 12 months [*TimingCube* is] up a remarkable 29.18% by *Hulbert Financial Digest* count, compared to a loss of 20.03% for the dividend-reinvested Wilshire 5000 Total Stock Market Index. Impressively, *TimingCube* also caught this year’s bounce-back. Over the year to date through July, the letter is up 33.3% versus 12.5% for the total return Wilshire 5000. And *TimingCube’s* success has been sustained for some time. Over the past three years, the letter has achieved a 5.19% annualized gain, versus negative 5.78% annualized for the total return Wilshire 5000. Over the past five years, the letter has achieved a 3.5% annualized gain against a 0.63% annualized gain for the total return Wilshire 5000.”
> >
> > “Black-box Letter Still Bullish on Stocks”: “Over the past 12 months… *TimingCube* is up 44.8% by *Hulbert Financial Digest* count, compared to negative 6.43% for the dividend-reinvested Wilshire 5000 Total Stock Market Index. And this success is sustained. Over the past three years, the letter is up an annualized 6.96% against negative 4.83% annualized for the total return Wilshire 5000. Since April 2003, when the *HFD* began following *TimingCube*, it’s up 11.1% annualized versus 5.4% annualized for the total return Wilshire 5000.”
>
> The *Hulbert Financial Digest* cumulative return measurement approach is very sensitive to measurement start and stop dates, more so than average return over many fixed intervals (days, months, years). Lucky starts (arguably prevalent due to survivorship bias) can dominate results for many years. Also, the reporting periods described in the above quotes are fairly short for measuring the performance of a service like that offered by *TimingCube*. The *Hulbert Financial Digest* results do not mean that *TimingCube* signals outperform 200-day SMA signals as described above.
>
> The performance of a market timing advisory service, even if its signals are random, depends substantially on the frequency and severity of bear market conditions. Even random timing signals, by sometimes specifying cash or short positions, will outperform buy-and-hold when the market is declining. The media may have a tendency to pay more attention to market timers during bear markets,

when they tend to have a “random” performance edge.

A reader followed up: “*TimingCube’s home page* claims a 37% annualized return. In prior years, they advertised 100%+ returns. For the first year I followed them (2003), they did great. I told everyone about it. Their subsequent failure starting in 2004 though has taught me a lesson. You have to give a system two full years at least to see if will work. I wish I had done that. Every single person to whom I recommended *TimingCube* has left them. If you look at *TimingCube’s results page*, you will see pure fiction. These are not the actual signals they put out, but instead the ‘revised’ signals that they backtested after the system failed a few times. I am surprised they are still in business. The SEC doesn’t respond to complaints very well. Why? There are lots of *TimingCube*s out there. It would be like reporting a dishonest used car salesman… Dishonesty and fraud is what *TimingCube* is about. …I wish you or someone would dig a little deeper and expose guys like this who misrepresent their results.”

> Presentation of backtested results, with trading frictions excluded, is common in marketing copy among informational services like *TimingCube*. It takes a degree of sophistication to understand the implications. The SEC apparently assumes that investors have this degree of sophistication, so disclosures and disclaimers (though generally much less prominent than marketing claims) protect the offerors.
>
> Over and over again, CXOadvisory.com, in both general commentaries and specific reviews, cautions about the bias involved in hypothetical backtests and about the potentially material impacts of trading frictions on returns (and sometimes the incredible extrapolations of very high returns). Over and over again, reviews point out that the disclaimers made by informational services conflict with the representations in their marketing copy. See Investing Demons for a comprehensive synthesis.
>
> It is difficult to understand why people ignore the flat disclaimers of usefulness and rigid disavowals of any warranty these services include on their sites. Would these same people buy cars or appliances with no performance guarantee (no warranty)?
>
> The SEC will act on hard evidence of intentional deception. See “What About Dan Murphy?” and “Safe with Martin Weiss?” for examples.
>
> Specifically, the above analysis uses older (and less prominent) trade data that *TimingCube* claims is not backtesting but live signals. Findings appear not to conflict with those cited in *MarketWatch* to *Hulbert Financial Digest*, which employs real-time testing with trading frictions. The CXOadvisory.com review also quotes *TimingCube*‘s disclaimer that their service is of any use and flat denial of warranty.
>
> Note that, depending on the frequency with which a trading system generates trading signals, the duration of the signals and any implicit relationship between the system and market/economic conditions, statistical confidence (to the extent such confidence is

achievable at all) may require sample periods much longer than two years.

Note also the following from Peter Brimelow in *MarketWatch* (12/23/10): “The Terrible Ten for 2010… TimingCube, F. Minssieux: -9.0%… Still, TimingCube is up 3.03% annualized over the last three years.”

Originally published at http://www.cxoadvisory.com/2774/technical-trading/timingcube-market-timing-advisory-service/ on December 18, 2009.

Combine Momentum with Low Volatility?

October 7, 2009

A reader commented and requested: "I got a lot of ideas from Michael Carr's recently published *Smarter Investing in Any Economy*, which focuses on momentum investing. One idea that the author demonstrated works well, and which I don't recall having been discussed on your web site, is that one can greatly reduce drawdowns in momentum investing, with little impact to returns, by accounting for volatility when determining Relative Strength. For example, defining a low-volatility Relative Strength as the six month return divided by the standard deviation seems to give a much better risk-adjusted reward than Relative Strength alone. If you read the book some time, I'd be interesting in your views on this. The author seems very diligent in thorough, professional testing (good sample sizes, out-of-sample verification, etc)."

Here are a few observations (based only on excerpts from the book derived from search terms).

The following formal research is relevant to the author's investigation of volatility-adjusted momentum, but it does not appear to address the volatility-momentum hypothesis directly. It offers an implication that adding a low-volatility screen to a momentum screen might help avoid stocks with the sharpest momentum reversals.

> "Price Momentum and Idiosyncratic Volatility" – "We find that returns to momentum investing are higher among high idiosyncratic volatility (IVol) stocks, especially high IVol losers. Higher IVol stocks also experience quicker and larger reversals. The findings are consistent with momentum profits being attributable to underreaction to firm-specific information and with IVol limiting arbitrage of the momentum effect. We also find a positive time-series relation between momentum returns and aggregate IVol. Given the long-term rise in IVol, this result helps explain the persistence of momentum profits since Jegadeesh and Titman's (1993) study."

The description of *Smarter Investing in Any Economy* states:

> "After running millions of relative strength calculations, Carr proves that relative strength investing works in any market climate. By strictly following his methodologies outlined in this book, you can more than double the returns of the S&P 500, with less risk… Computing advances, coupled with new ETFs that limit risk have made relative strength a viable strategy for long-term investors and day traders alike."

"Millions" of calculations raises the flag of data snooping (mining) bias. Using the Amazon.com capability to search the book for references to “data mining” generates:

> Page 26: “Many investment strategies are based upon data mining – sifting through the mountains of market data available to discover what worked in the past in the hopes that it will work in the future. RS [Relative Strength] is different than most data mining strategies, because economic theory and experience confirms that it works.”
>
> Page 104: “To provide the best answer possible, we tested all possible combinations… In all, 1,320 combinations were tested. One problem that can occur when so many possibilities are tested is that the results from the top-performing strategy will be superior to all other test results because of a statistical fluke. Running hundreds of tests to identify trading rules is known as data mining. This term refers to the idea of sifting through large amounts of data…and identifying potentially useful, but accidental relationships within the data. The danger is that in a very large set of data, there is the possibility that extremely rare events will occur…and as such they are unlikely to be available to investors in the future.”
>
> Page 105: “To guard against potential data mining, we will perform several tests to ensure the result is due to the underlying logic of the trading rules.”
>
> Page 144: “Some investors think that optimization is similar to data mining. As discussed earlier, this is not true. An exercise in data mining would be to find the stocks that performed the best week to week and then go back and identify characteristics to explain why this occurred.”
>
> Page 145: “We began our system design with solid underlying logic…and we then tested the logic under a variety of conditions. That is the opposite of data mining.”

These excerpts and other material available via the Amazon.com search function (e.g., a search on “normal distribution”) raise some cautions:

1. The relationship between economic theory and empirical evidence is an uneasy one. The quality of empirical evidence is mixed. Momentum seems to be one of the more reliable asset price effects, but the assertion “economic theory and experience confirms that it works” is too strong. Browse “Blog Synthesis: Momentum Investing/Trading” for some different explanations of momentum and for examples of momentum variability/instability. It seems fair to say that luck is more pervasive than momentum.
2. The degree to which studies of momentum for individual stocks translate to ETFs, which subsume the trading frictions of portfolio rebalancing (and add a management fee), is not obvious. ETFs have not been around long enough to support rigorous momentum testing.
3. The author’s treatment of data mining appears to be incomplete. The effects of data mining bias are generally more systematic than rare event capture and spurious hypothesis acceptance. Running different kinds of tests helps, but parameter optimizations do generally impound data mining bias. For example, regarding the quote from Page 104, there are statistical methods to correct for the data mining bias impounded in outcomes from a specific number of tested combinations (in this case,

1,320). See the summaries of Chapters 6 and 8 in “*Evidence-Based Technical Analysis: Applying the Scientific Method and Statistical Inference to Trading Signals* (Chapter-by-Chapter Review)”.

4. The author appears to rely on the normality of return distributions (e.g., in interpreting standard deviation), but there is much evidence that equity return distributions are not normal. See “*The Black Swan: The Impact of the Highly Improbable* (Chapter-by-Chapter Review)”. The “wildness” of actual return distributions can disrupt trading strategies that make an assumption of normality.

Searches in the book via Amazon.com on “transaction costs” are not illuminating. Momentum strategies applied to individual stocks tend to involve substantial trading frictions from portfolio rebalancing. Assumptions about these frictions can be crucial in translating tests to realistic expectations.

Best guess is that combining low volatility with high momentum might offer an edge but that any edge will not be as large/reliable as indicated in the book.

Mal Williams reported the following test results for his momentum-based asset class rotation strategy (see “An Investor’s Asset Class Momentum Trading Strategy”):

> “A few years ago, I tried the exact same strategy of dividing the momentum calculations by the standard deviation to arrive at a volatility-adjusted momentum calculation. In fact, I still have a column for the volatility adjusted momentum each month in my monthly report. Unfortunately, the results obtained from my COP [Class OutPerformance] Research model showed a significantly lower return without a commensurately lower portfolio volatility.”

Michael Carr, the author of *Smarter Investing in Any Economy*, declined an offer to append here any substantive response he might have to the above comments. He regards commenting on the book without reading it in its entirety as intellectually lazy, irresponsible and unprofessional.

The approach used above to develop a quick reaction to the book uses the Amazon.com search function to focus on practices and assumptions that may cause backtests to overstate real, out-of-sample performance of investing strategies.

Readers can decide for themselves whether the approach has merit in screening books for reading.

The reader posing the original question added:

"Since the author of the Class OutPerformance strategy got quite different results than Michael Carr, I suspect the differences are due to other factors then the just the momentum formula, such as how often was trading done, what was the buy signal, what was the sell signal, how many funds were held at once, and so forth. Here are some specifics from Carr's book on how adjusting for volatility helped:

"The initial data set consisted of 33 Fidelity Select Sector Funds. The tests were run from 01/01/1990 through 12/31/2007. The relative strength in test 1 was the 26 week rate of change. The relative strength in test 2 was the 26 week rate of change divided by the 26 week standard deviation. Friday closing prices were used for ranking (Thursday if Friday was a holiday), with trades executed on the Monday open. Initially, the top three ranked funds were bought. They were held as long as they were in the top half (top 17 of 33) rank. If they dropped below 17th place, they were replaced by the current top ranked fund. The results were as follows:

Test 1: Annualized return = 20.10%, Max drawdown = -52.26%

Test 2: Annualized return = 18.93%, Max drawdown = -27.18%

"A number of other tests were done, showing that holding the top 3 funds, and selling if they dropped out of the top 50%, is not at all optimized. Turns out that holding the top single fund is best.

"Tests in which the fund set contained money market funds and bear funds did poorly (worse returns and higher risk than the S&P 500 Index). Much of the momentum benefit apparently depends on the having the right kinds of funds in the fund set. Anyway, I'd recommend reading the book because there is too much detail to easily summarize in a brief space. For example the author studies a wide variety of momentum formulas, both adjusted for risk and not, and shows that some of the classic ones are not very good."

Note that the sample period is not very long for 26-week momentum measurement testing. It consists of only 18 years (about 36 completely independent 26-week intervals). There may have been external peculiarities (e.g., secular disinflation) that relate to the hypothesized anomaly (momentum).

Note also that when results are not robust to different parameter settings or other choices not excluded by the basic hypothesized anomaly, such as which funds to use, elevated concern about data snooping (mining) bias is warranted. In other words, when some combinations work and others do not, it is reasonable to worry whether the best combinations work mostly because of luck rather than persistent anomaly. As noted above, there are statistical techniques that help filter out the luck.

Subsequently, Michael Carr, the author of *Smarter Investing in Any Economy*, wrote **[items in**

bolded brackets added]:

"Please stop commenting on my work and post this email only in its entirity **[sic]** if you do so.

"You wrote:

> 'Note that the sample period is not very long for 26-week momentum measurement testing. It consists of only 18 years (about 36 completely independent 26-week intervals). There may have been external peculiarities (e.g., secular disinflation) that relate to the hypothesized anomaly (momentum).
>
> 'Note also that when results are not robust to different parameter settings or other choices not excluded by the basic hypothesized anomaly, such as which funds to use, elevated concern about data snooping (mining) bias is warranted. In other words, when some combinations work and others do not, it is reasonable to worry whether the best combinations work mostly because of luck rather than persistent anomaly. As noted above, there are statistical techniques that help filter out the luck.'

"1) People don't invest for independent 26-week cycles – they invest for the 18 years. And, the method I used follows standard academic protocols, as you'd know if youe **[sic]** read the book. **[The note relates to sample size relative to parameter measurement interval and the associated inherent reliability of inference, not investing assumptions. For some interesting discussions of how timeframes might affect inferences, see "Basic Equity Return Statistics" and "Why the Story on Predictability Keeps Changing".]**

"2) I test for parameter sensitivity, as you'd know if you read the book. **[The note relates to the risk of data snooping bias when testing many parameter settings within rules, many rules or many combinations of rules. See the summary of Chapter 6 in "*Evidence-Based Technical Analysis: Applying the Scientific Method and Statistical Inference to Trading Signals* (Chapter-by-Chapter Review)" for elaboration.]**

"Your conclusions are half-baked and I will not offer substantial comments because you don't just get to say dumb things and create work for those of us actually earning a living in the markets. **[The first amendment to the U.S. Constitution accommodates the saying of many dumb things. And, those encountering sayings they deem dumb have a choice to ignore them.]**

"Again, raed **[sic]** the book or stop commenting."

Originally published at http://www.cxoadvisory.com/3003/momentum-investing/combine-momentum-with-low-volatility/ on October 7, 2009.

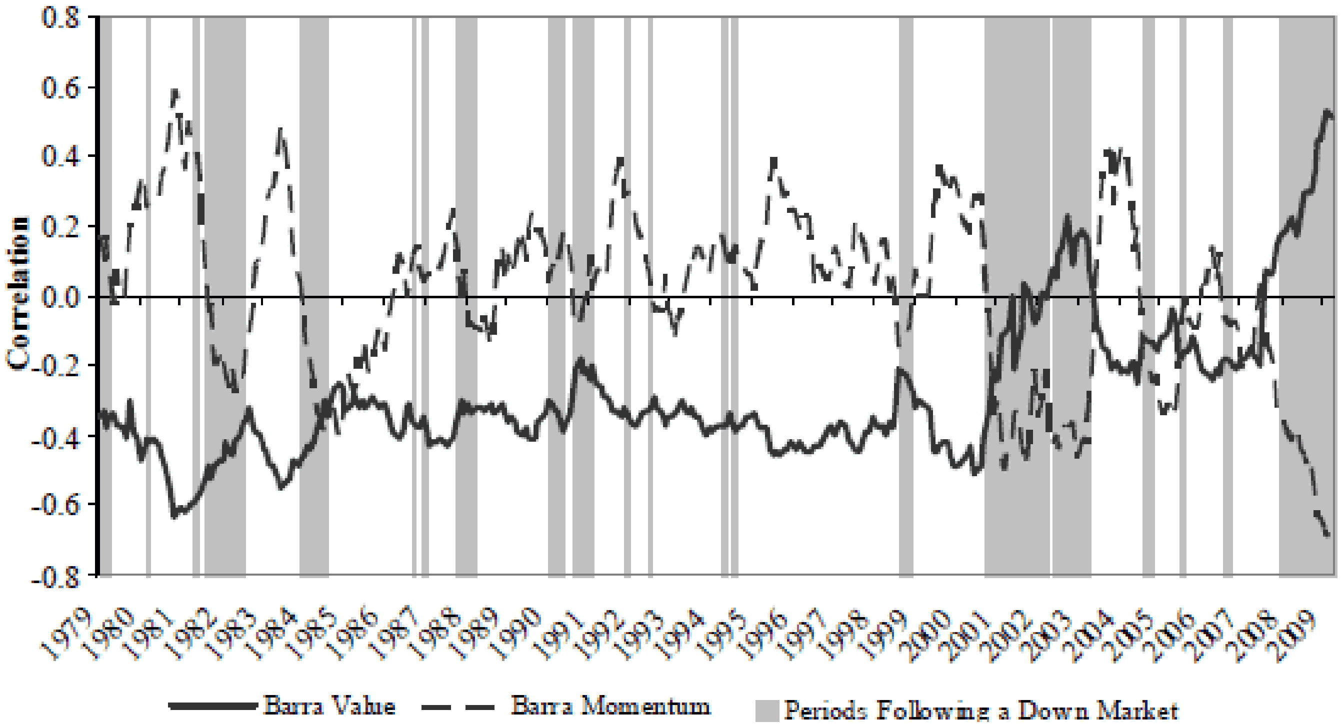
Upside Down Beta Distributions for Value and Momentum?

September 24, 2009

Typically, value means unexciting low-beta stocks, and momentum means exciting high-beta stocks. Does “typically” mean always? In their September 2009 paper entitled “The Changing Beta of Value and Momentum Stocks”, Andrea Au and Robert Shapiro investigate the relationships between beta and value and between beta and momentum under varying stock market conditions. Using monthly beta distributions for value (based on book-to-market ratio) and momentum (based on prior 12-month return) sorts of the Russell 3000 stocks over the period December 1978 through March 2009, *they conclude that:*

- Historically, high value (momentum) stocks are typically low (higher) beta stocks.
- However, during the past couple of years, high value (momentum) stocks have become high (relatively lower) beta stocks. This flip-flop recently reached an extreme not seen in at least 30 years (see chart below).
- During such extremely abnormal intervals:
    - Hedged value strategies (value minus growth) dramatically outperform a rising market and dramatically underperform a falling market.
    - Hedged momentum strategies (high minus low) underperform a rising market and outperform a falling market.
- Under such conditions, overweighting value (momentum) amounts to an unintended bet on a recovering (relapsing) market.

The following chart, taken from the paper, tracks the correlation between book-to-market ratio and beta (Barra Value) and the correlation between 12-month momentum and beta (Barra Momentum) based on monthly measurements of Russell 3000 stocks over the past 30 years. Gray shading indicates intervals following negative market returns over the preceding six months. During early 2009, the correlations exhibit an extreme flip-flop, such that high value (momentum) stocks now tend to have high (relatively low) betas.



In summary, *value-beta and momentum-beta relationships can and recently have reached such extremes that value and momentum strategies may impound untended assumptions about the future market trend.*

Originally published at http://www.cxoadvisory.com/2245/value-premium/upside-down-beta-distributions-for-value-and-momentum/ on September 24, 2009.

Any Tools to Implement Value-Momentum Asset Class Allocation?

September 23, 2009

A reader asked: "Regarding 'Combined Value-Momentum Tactical Asset Class Allocation', have you developed any sort of screen or model that ranks value exactly as studied in the referenced paper (asset yield or earnings yield)?"

The authors of the paper referenced in the summary you cite consider 12 asset classes: three U. S. equity classes, three international equity classes; three U.S. bond classes, two international bond classes and the risk-free rate. They describe their approach to comparing value across these 12 classes as follows:

> "The starting point of our approach is to take a simple yield measure for each asset class. For equity assets we take the (trailing) earnings yield (E/P ratio), while for bond assets we take the standard yield-to-maturity. Both yield measures are adjusted for the appropriate (local) risk-free rate of return…this means that we are effectively taking the term premium as our valuation indicator.
>
> "…we apply a limited number of asset-specific, fixed adjustments to the basic yield data. These adjustments were chosen in such a way that the main structural biases towards certain asset classes are removed. Specifically:
>
> - for the government bond assets, US Treasuries and German and Japanese government bonds, we subtract 1% from the term premiums, which adjusts for the fact that the yield curve tends to be upward sloping;
> - for US investment grade credits we subtract 2% and for US high yield bonds 6%, also to adjust for the slope of the yield curve, and additionally to adjust for default risk;
> - for emerging markets equities we subtract 1% to adjust for the structurally lower P/E compared to mature equity markets;
> - for US real estate equities we subtract 2% to adjust for the structurally higher yield compared to regular equities.
>
> "…these adjustments result in [valuation] scores that are much more comparable across asset classes. In fact, after applying the adjustments, the long-term average valuation score for every asset falls in a range between -1% and +1%, which implies that structural biases towards certain asset classes are effectively eliminated."

The authors then combine the resulting asset class valuation ranking with an asset class price momentum ranking to determine the most attractive asset classes.

While the approach appears straightforward and the data generally available, CXOadvisory.com has not developed any screens or models to implement or replicate this approach.

One could perhaps add commodity futures to the set of considered asset classes via valuation scores related to an adjusted roll yield for individual or groups of commodities.

Originally published at http://www.cxoadvisory.com/2979/value-premium/any-tools-to-implement-value-momentum-asset-class-allocation/ on September 23, 2009.

Why the Skip-period in Momentum Strategies?

September 14, 2009

A reader asked: “In reviewing your various posts on momentum-based trading, I noticed that many impose a one-month delay between momentum calculation and actual trade implementation. Is the effect/rational for this strategy adjustment referenced anywhere or is this something you can comment on?”

The original momentum research (Jegadeesh and Titman, 1993, “Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency,” Journal of Finance 48, pp 65- 91) introduced a skip-period as an alternative momentum strategy. The rationale is as follows (from the 2001 paper entitled “Momentum” by Jegadeesh and Titman):

> “Jegadeesh (1990) and Lehmann (1990) examine the performance of trading strategies based on one week to one month returns and find that these short horizon strategies yield contrarian profits over the next one week to one month…
>
> “…Jegadeesh and Titman (JT) (1993) examine the performance of trading strategies with formation and holding periods between three and 12 months. Their strategy selects stocks on the basis of returns over the past J months and holds them for K months. This J-month/K-month strategy is constructed as follows: At the beginning of each month t, securities are ranked in ascending order on the basis of their returns in the past J months. Based on these rankings, JT form ten equally weighted decile portfolios. The portfolio with the highest return is called the ‘winners’ decile and the portfolio with the lowest return is called the ‘losers’ decile.
>
> “Jegadeesh and Titman (1993) examine U.S. stocks during the 1965 to 1989 period. Table I reports the average returns of the different buy and sell portfolios as well as the zero-cost, winners minus losers portfolio, for the strategies described above. All strategies considered here earn positive returns. The table also presents the returns for a second set of strategies that skip a week between the portfolio formation period and holding period. By skipping a week, these strategies avoid some of the bid-ask spread, price pressure, and lagged reaction effects documented in Jegadeesh (1990) and Lehmann (1990).”

The rationale is recognition of a short-term reaction for stocks with momentum concentrated in a recent interval. Many subsequent papers and analyses are extensions or recent tests of the original findings. Some include a skip-period (a month for those using monthly data) in their strategies, and others do not.

Reader Mal Williams reported that he has tested his momentum-based asset class rotation strategy (see “An Investor’s Asset Class Momentum Trading Strategy”) with and without a skip period, and that it performs better without by about 2% annually over 19 years.

It may be that the original finding is a result of data mining or that skip-periods do not apply for monthly intervals.

Originally published at http://www.cxoadvisory.com/2932/momentum-investing/why-the-skip-period-in-momentum-strategies/ on September 14, 2009.

Have You Looked at ETFtradingstrategies.com?

September 6, 2009

A reader asked: “Have you ever looked at the work of David Vomund at ETFtradingstrategies.com?”

ETFtradingstrategies.com is an adjunct to the book *ETF Trading Strategies Revealed*, which “presents simple but highly effective mechanical ETF rotation techniques. The strategies use relative strength reports to rotate to strong areas of the market.”

Based on the information on the web site, the overall approach appears similar to those of the five asset class momentum strategies noted in “Some Best Guesses on What Works Best”. Momentum in asset prices appears to be fairly pervasive, as indicated by an extensive stream of formal research. In other words, the beliefs that appear to motivate the approach described on the web site have support from research.

Unlike the approach described at ETFtradingstrategies.com, which appears to view going to cash as a market timing decision rather than a momentum decision, some asset class momentum strategies treat cash as an asset class to which one rotates when it is the strongest class.

With respect to the returns reported for the six specific strategies tracked on the site, reasonable cautions would be:

- The backtest samples are fairly small, so statistical inference from them weak.
- Because data snooping bias is likely impounded in the strategy selection process, it is reasonable to assume that out-of-sample performance of these strategies will generally be weaker than the backtested results.
- Broad interest and activity in ETF-based momentum strategies may suppress their future returns as more and more investors compete for the returns.
- Have the authors accounted for trading friction (transaction fees, bid-ask spreads)? The more frequent the rebalancing specified for a strategy (and the smaller one’s account), the greater the impact of trading friction on net returns.
- Taxes from trading are a consideration if executing the strategies in a taxable account.

Originally published at http://www.cxoadvisory.com/2917/momentum-investing/have-you-looked-at-etftradingstrategies-com/ on September 6, 2009.

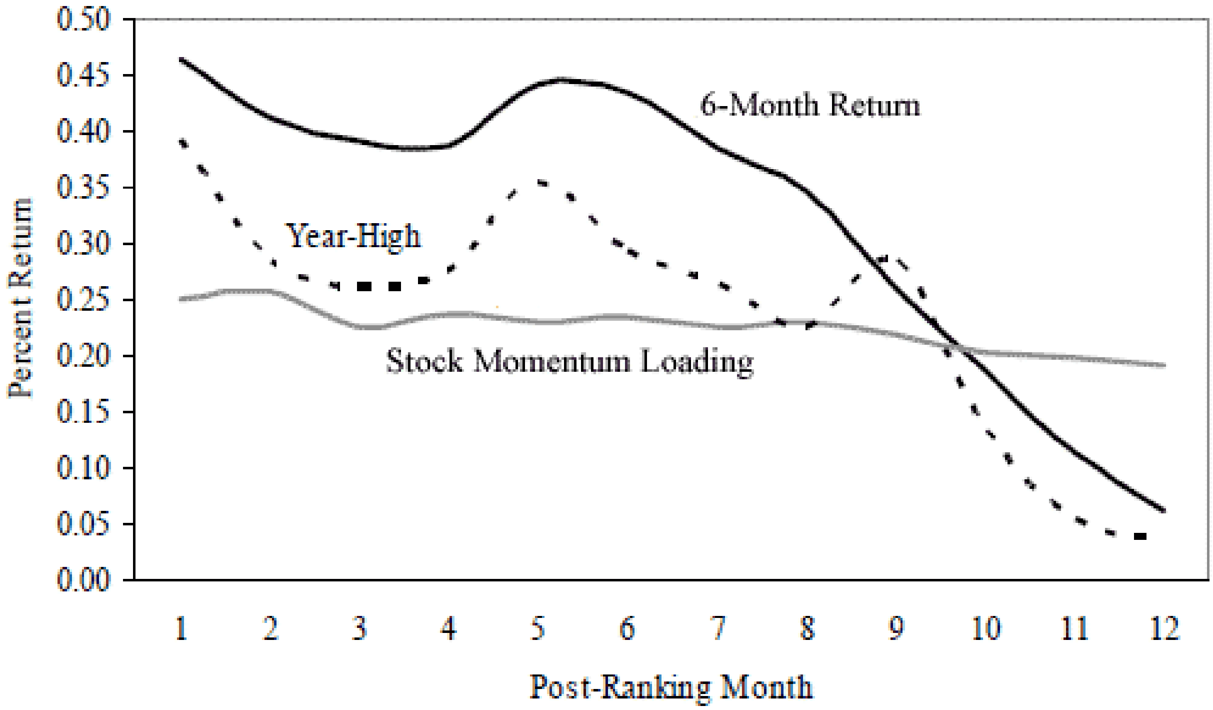
Mutual Fund Momentum Measure Fly-off

September 1, 2009

Which measure of mutual fund momentum best predicts future fund returns? In his August 2009 paper entitled "The 52-Week High, Momentum, and Predicting Mutual Fund Returns", Travis Sapp examines the intermediate-term future performance of mutual funds ranked by: (1) nearness to the one-year high of the fund share net asset value; (2) prior six-month fund return; and, (3) fund sensitivity to stock return momentum. Using mutual fund returns for a broad sample of U.S. common stock funds and risk-adjustment data over the period 1970-2004, *he concludes that:*

- All three momentum measures have significant, independent power to predict fund returns.
  - A strategy which buys the top 10% of funds and holds them for six months earns annualized risk-adjusted (for the Fama-French market, size and value factors) excess returns of 4.9%, 2.9% and 3.6% when ranking based on nearness to the one-year high, prior six-month return and sensitivity to stock return momentum, respectively.
  - A strategy which buys the top 30% of funds and holds them for six months earns annualized risk-adjusted excess returns of 2.9%, 1.6%, and 2.4% when ranking based on nearness to the one-year high, prior six-month return and and sensitivity to stock return momentum, respectively.
- Outperformance based on six-month returns are generally the largest, but this outperformance (along with that based on the nearness to the one-year high) tends to disappear 12 months after fund ranking. Outperformance based on sensitivity to stock return momentum is the smallest but least transitory. (See the chart below.)
- Nearness to the one-year high and past six-month return are significant predictors of monthly fund flows, whereas sensitivity to stock return momentum is not. In other words, investors appear to chase the two more transitory indicators of fund momentum.

The following chart, taken from the paper, shows the evolving risk-adjusted monthly returns for strategies that buy the top 10% of funds according to each of the three momentum rankings: (1) nearness to the one-year high of the fund share net asset value; (2) prior six-month fund return; and, (3) fund sensitivity to stock return momentum. For each post-ranking horizon, the return shown is the monthly alpha with respect to the Fama-French factors. The strategy based on past six-month fund return dominates initially, but the more abstract sensitivity to stock return momentum is more stable and persistent.



In summary, *evidence suggests that past six-month fund return is a stronger indicator of mutual fund momentum than either nearness of fund net asset value to its one-year high or a more abstract sensitivity of fund returns to stock return momentum.*

Originally published at http://www.cxoadvisory.com/2224/mutual-hedge-funds/mutual-fund-momentum-measure-fly-off/ on September 1, 2009.

Enhancing Asset Class Momentum with Downside Risk Avoidance?

August 28, 2009

A reader wondered about the value of combining momentum and downside risk avoidance for tactical asset class allocation, as follows:

> "One of the methods described in *The Ivy Portfolio* by Mebane Faber is a simple momentum-based asset class rotation system that shifts monthly into the one, two or three highest performing asset classes based on their performance over an average of the prior 3, 6 and 12 months. Instead of using just the 3, 6 and 12 month prior returns, what if we used an asset class Ulcer Performance Index (UPI): UPI = average return over prior 3, 6 and 12 months / average Ulcer Index (UI) over prior 3, 6 and 12 months. Would this modification identify which asset classes are in low-volatility uptrends and therefore the biggest bang for the buck? Would this allow us to invest comfortably in the top two asset classes, or even the top one asset class, instead of the top three as recommended by Faber?"

Calculation of UI over a rolling interval across a long sample period is cumbersome. As a substitute for UI, we use a standard deviation of downside weekly returns over past intervals for three asset classes: S&P Depository Receipts (SPY), iShares Barclays 20+ Year Treasury Bond (TLT) and iShares Russell 2000 Index (IWM) , with historical data limited to July 2002 (by TLT). Every four weeks, we allocate funds to whichever of SPY, TLT or IWM has the highest ratio of prior return to prior downside standard deviation, or to 13-week Treasury bills (T-bills) if all three past returns are less than the T-bill yield. Using weekly adjusted closes for the asset class proxies over the period 7/31/02 through 8/21/09 (369 weeks or about 89 months), *we find that:*

In calculating a standard deviation of downside weekly returns over an interval, we set the weekly return to its actual value when the return is negative and to 0% when the return is positive. The ratio of prior return to prior downside standard deviation is generally more discriminating (has larger range across asset classes) than prior return alone.

For an initial test, we use only 13-week lagged metrics for asset allocation signals, 13-week past return and downside standard deviation of weekly returns over the past 13 weeks. The following chart summarizes average 4-week returns and variabilities for seven cases over the entire sample period for this one-interval test, as follows:

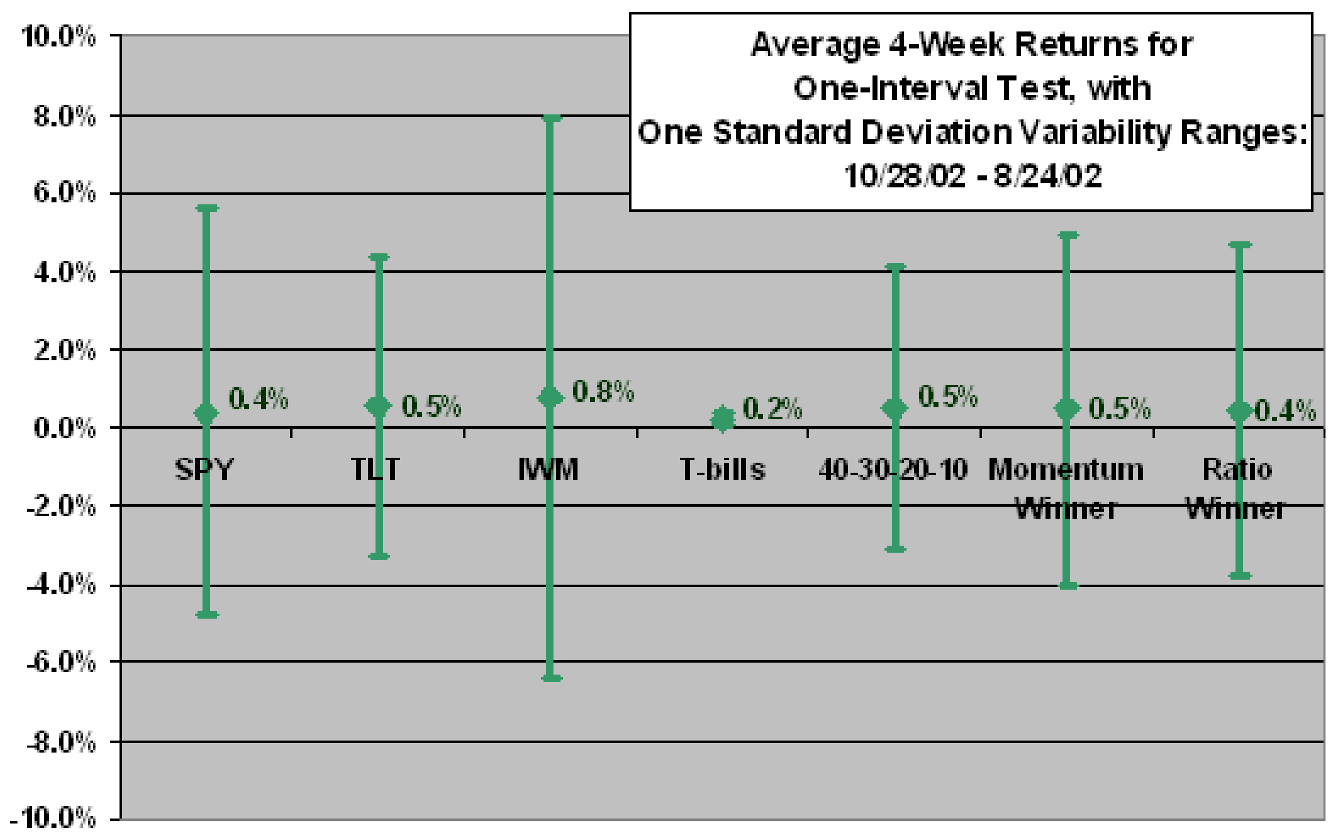
- Buy and hold SPY.
- Buy and hold TLT.
- Buy and hold IWM.

- Hold T-bills continuously.
- Allocate 40%-30%-20%-10% to SPY-TLT-IWM-Cash, rebalancing every four weeks at the close (40-30-20-10).
- Allocate all funds every four weeks at the close to SPY, TLT, IWM or T-bills based on the highest lagged 13-week return (Momentum Winner).
- Allocate all funds every four weeks at the close to SPY, TLT or IWM based on the highest ratio of lagged 13-week return to lagged 13-week downside standard deviation, or to T-bills if the T-bill yield bears the three returns (Ratio Winner).

The start date of 10/28/02 is based on calculation of 13-week lagged metrics starting 7/31/02.

The winner of this one-interval test based on average 4-week return is buy-and-hold IWM; however, this case also has the highest standard deviation of returns. The other cases are closely bunched. The Ratio Winner has slightly lower average 4-week return and standard deviation of 4-week returns than does the Momentum Winner. The fixed 40-30-20-10 asset allocation approach offers the lowest portfolio variability.

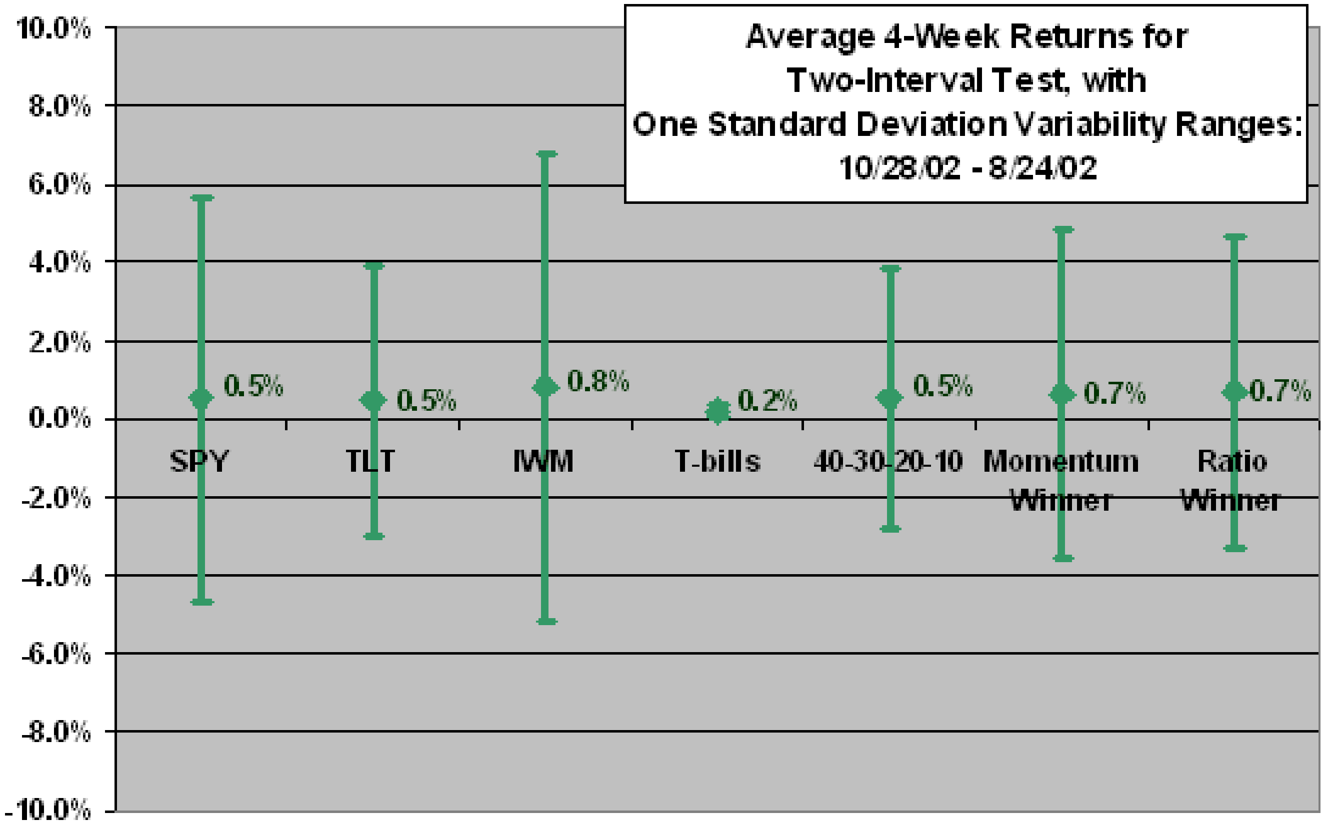
What happens if we use the average of 13-week and 26-week prior returns and the average of 13-week and 26-week prior downside standard deviations instead of just the 13-week lagged results?



The next chart summarizes average 4-week returns and variabilities for the seven cases over the entire sample period based on averages of 13-week and 26-week lagged metrics. The start date of this two-interval analysis is 2/3/03 based on calculation of 26-week lagged metrics starting 7/31/02.

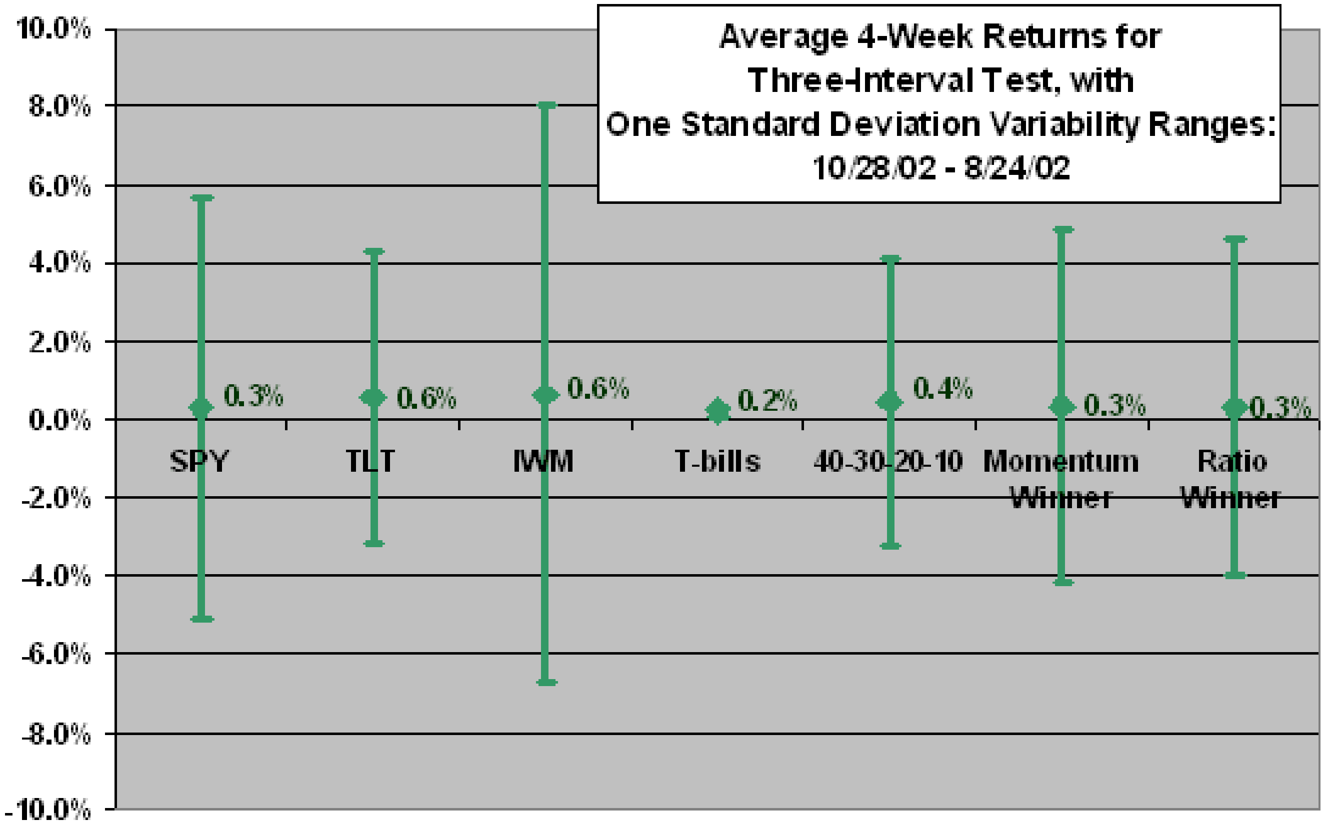
For this two-interval test, the Momentum Winner and Ratio Winner strategies perform similarly and relatively well in comparison with the 40-30-20-10 strategy and the passive strategies.

What happens if we use the average of 13-week, 26-week and 52-week prior returns and the average of 13-week, 26-week and 52-week prior downside standard deviations?



The final chart summarizes average 4-week returns and variabilities for the seven cases over the entire sample period based on averages of 13-week, 26-week and 52-week lagged metrics. The start date of this three-interval analysis is 8/4/03 based on calculation of 26-week lagged metrics starting 7/31/02.

For this three-interval test, the Momentum Winner and Ratio Winner strategies perform similarly but are not strong in comparison with the 40-30-20-10 strategy and some of the passive strategies. It may be that the quicker reactions of the shorter-cycle momentum intervals used above have been better suited to the elevated volatility of the recent bear market.



Note that:

These analyses assume no trading frictions, which would generally be modest for the securities and rebalancing/reallocation frequencies used. However, for small accounts, trading frictions could materially reduce average returns for strategies requiring trading.

The analysis ignores the tax implications of trading, which could be substantial for investors using taxable accounts.

This sample period (spanning roughly one bull and one bear market) is short for evaluating asset class allocation strategies, as suggested by the disparities in results across the three tests. There are only about seven completely independent 52-week intervals in the sample. Testing across multiple business (interest rate) cycles is desirable.

Including more asset classes may improve the performance of the three asset allocation approaches above. Holding multiple asset class winners (rather than just one winner) from a larger selection may hurt or help average returns.

Other ways of calculating downside risk and other combinations of lagged return and downside risk may produce different results. Testing different parameters/ parameter settings across the same data set introduces data snooping bias into the distribution of results across cases.

In summary, *evidence from simple tests does not support a belief that adding a downside risk factor materially enhances the performance of a momentum-driven tactical asset class allocation strategy.*

Originally published at http://www.cxoadvisory.com/4213/technical-trading/enhancing-asset-class-momentum-with-downside-risk-avoidance/ on August 28, 2009.

Interplay of Beta with Momentum and Contrarian Investing

August 27, 2009

Does momentum trading (and its contrarian counterpart) work better for certain kinds of stocks? In their August 2009 paper entitled "Systematic Risk and the Performance of Mutual Funds Pursuing Momentum and Contrarian Trades", Grant Cullen, Dominic Gasbarro, Gary Monroe and Kenton Zumwalt examine mutual fund trading activity and performance to measure the prevalence of and results for momentum and contrarian equity investing strategies. Using the quarterly stock holdings of 2,829 U.S. equity mutual funds and associated stock price data for the period 1991-2006, *they conclude that:*

- About 15% (14%) of equity mutual funds substantially follow a momentum (contrarian) trading strategy.
- These contrarian and momentum trading behaviors tend to persist over time.
- Based on simple excess returns, the contrarian strategy beats the momentum strategy on average by 2.2% and 2.5% over post-trade horizons of three and six months, respectively. Outperformance is robust to previous fund return, fund portfolio turnover, fund size and fund portfolio liquidity. However, outperformance disappears on a four-factor (market, size, value and momentum) adjusted basis.
- Mutual funds following a momentum strategy improve their performance by buying (selling) high-beta stocks that have been recent winners (losers). Similar funds that trade low-beta stocks hurt their performance.
- Conversely, funds following a contrarian strategy improve their performance by buying (selling) low-beta stocks that have been recent losers (winners). Similar funds that trade high-beta stocks hurt their performance.
- A possible explanation for these beta-related effects is that pricing for low-risk stocks is more efficient than that for high-risk stocks. Reversion to intrinsic value is therefore faster for low-beta than high-beta stocks, which tend to be small, thinly traded and meagerly covered by analysts.

In summary, *evidence from mutual funds suggests that momentum (contrarian) investors/traders can enhance returns by focusing on stocks with high (low) beta.*

Originally published at http://www.cxoadvisory.com/2221/volatility-effects/interplay-of-beta-with-momentum-and-contrarian-investing/ on August 27, 2009.

A Few Notes on Quantitative Strategies for Achieving Alpha

July 20, 2009

In his 2009 book, *Quantitative Strategies for Achieving Alpha*, flagged by Jeff Partlow, author Richard Tortoriello "seeks to determine *empirically* the major fundamental and market-based drivers of future stock market returns" by testing over 1,200 alternative investment strategies. He believes "that the quantitative approaches outlined in this book can provide a proven way to generate investment ideas for the qualitative investor as well as a discipline that can help improve investment results." Richard Tortoriello is an equity research analyst with Standard & Poor's. The *principal elements of the book are:*

Chapter 2: This chapter outlines the methodology applied in the book, as follows:

- The sample period is 1987-2006.
- The sample is about 2,200 public companies per year, trimmed in various ways to avoid "bad behavior," such as that exhibited by microcaps and very low-priced stocks, with attention to survivorship bias and look-ahead bias.
- The equal-weighted portfolio rebalancing period is 12 months.
- Sorting into quintiles (five equal partitions) along the parameter(s) of interest is central to the analyses.
- Ignore trading frictions.

A strong strategy is one for which: (1) The top (bottom) quintile significantly outperforms (underperforms) the overall sample; (2) the progression of excess returns across quintiles is systematic; (3) results are reasonably consistent over time during the sample period; and, (4) return volatility and maximum loss are reasonably low. There is no guarantee that strong strategies will continue to be strong in the future.

Chapter 3: Earnings growth and free cash flow growth are the key fundamental drivers of stock market returns, with the market efficiently incorporating the former but not the latter. The price-to-forward earnings estimate ratio is the strongest sentiment-related driver of stock market returns.

Chapters 4-10: These seven chapters provide quantitative portfolio results based on the methodology of Chapter 2 for investment strategies based on one or two indicators from among the following categories: profitability; valuation; cash flow; growth; capital allocation; price momentum; and, red flags.

Chapters 11-13: These chapters synthesize the outputs of Chapters 4-10 by providing guidance on development of an integrated investment model. Chapter 11 asserts that:

> "To be successful, the common stock investor must answer three essential questions about any potential investment, with a relatively high degree of certainty: (1) Is the business doing well? (2) Is the valuation attractive? and (3) Is the timing, in terms of the overall stock market and the individual stock supply / demand trends, right?"

Chapter 12 offers some rankings of the best previously tested single-indicator and dual-indicator strategies based on specific performance metrics. Chapter 13 offers some example stock screens.

Appendix A (B) ranks the performance of 42 single-indicators (65 dual-indicator) stock sorting strategies several ways. **Appendix C** provides a few statistics for 43 indicators by year during 1987-2007.

Some critiques of the book are as follows:

> The book seems myopic with respect to asset classes, focusing exclusively on a subset of U.S. equities. Asset class allocation is arguably more important than stock selection for overall investing success.
>
> The strategies presented in the book involve holding a reasonably large number of individual stocks to achieve statistical reliability. Even for annual rebalancing and especially for small investors, who can allocate only modest amounts to each stock in a diversified portfolio, trading (and shorting) frictions would likely dent the alphas reported materially.
>
> The 1987-2006 sample period coincides with a secular disinflationary environment in the U.S. that probably favored equities in general and perhaps affected specific equity screening strategies. This environment seems unlikely to persist. More generally, as acknowledged by the author, the market may be adaptive such that strategies that work historically work less well in the future.
>
> The data snooping bias derived from testing "over 1,200 investment strategies" is also likely material, despite the mitigations offered by multiple tests and triangulations. The book offers no corrections to screen out the luck impounded by selecting the best-performing strategies from such a large pool. This bias leads to overstated alphas. The pre-emptive statement in the book that "almost all of the tests we undertook are based on existing financial and investment theory" is weak because of the generally modest and often unstable predictive power of hypotheses derived from "financial and investment theory."
>
> Like many comparable books and studies, this book implicitly accepts the normality (or at least non-wildness) of stock return distributions. There is a reasonable body of evidence that stock returns may be wild, such that mean returns are unstable and volatility statistics such as standard deviation and Sharpe ratio lose their "normal" meanings.

> There is an argument to be made that investors experiencing investments in real time, because of uncertainties in expectations, rationally perceive anomalies differently from those hypothesizing in hindsight.

In summary, Quantitative Strategies for Achieving Alpha *offers an interesting quantified overview of the performance of various fundamental, sentiment and technical indicators with respect to U.S. stock sorts over the past generation. However, investors should probably assume that the results materially overstate the size of these indicator alphas.*

Originally published at http://www.cxoadvisory.com/2704/fundamental-valuation/a-few-notes-on-quantitative-strategies-for-achieving-alpha/ on July 20, 2009.

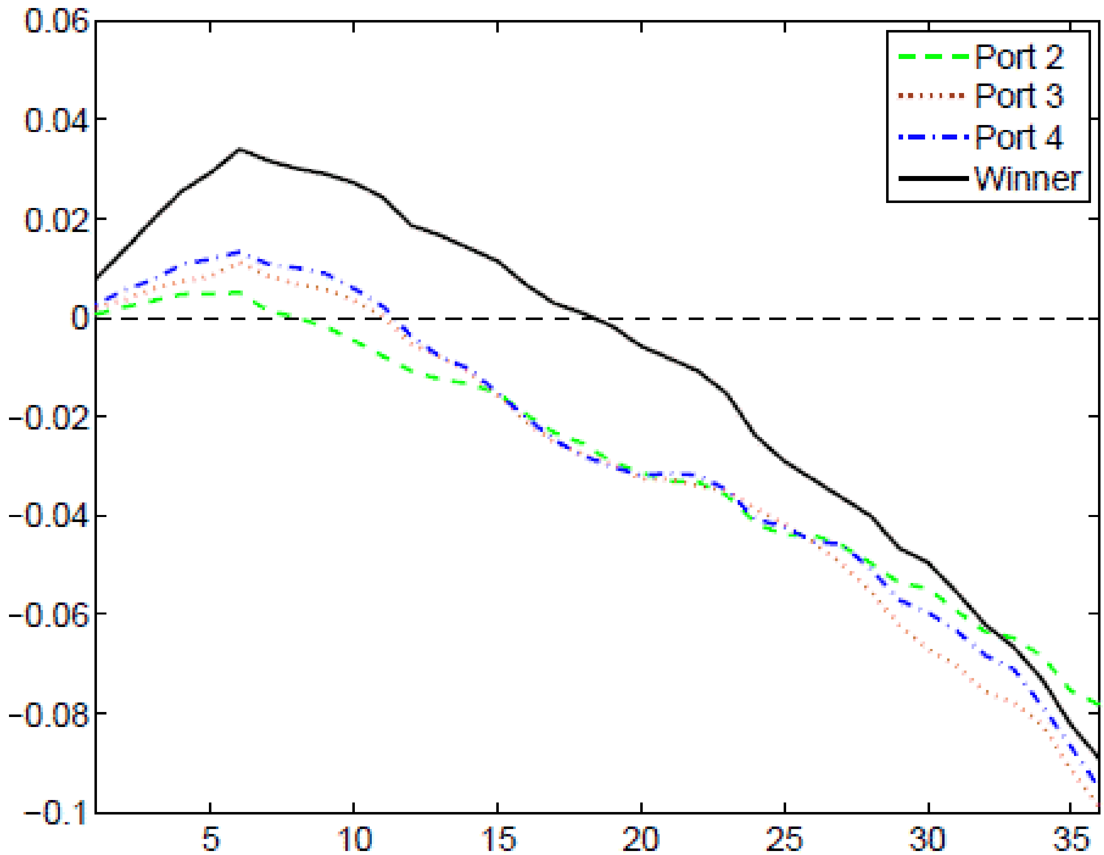
Momentum a Big Mistake?

July 7, 2009

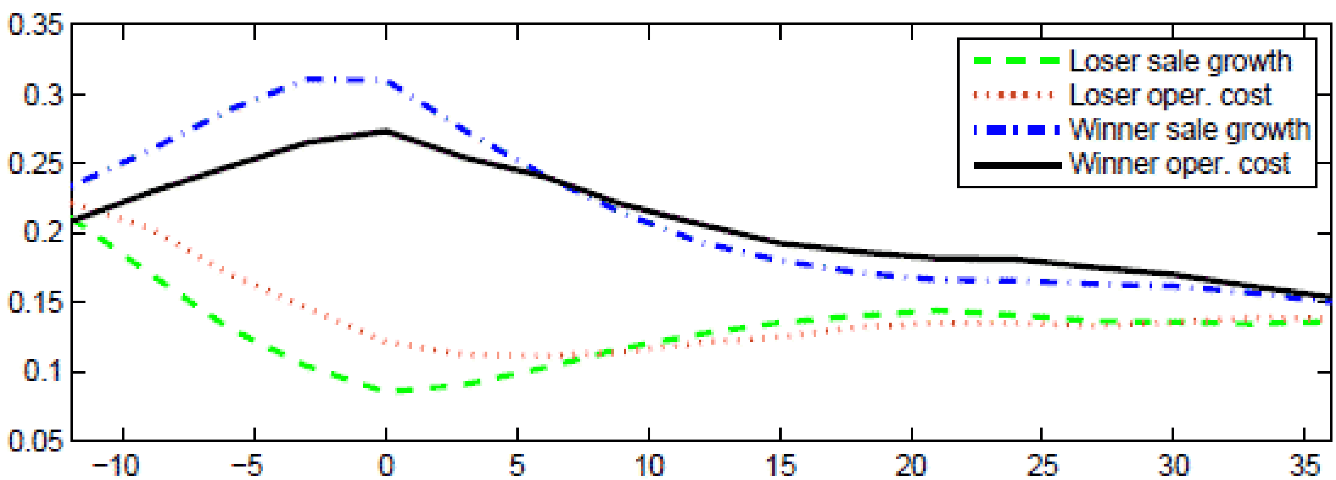
Is chasing returns a bet on rational analysis or investor overreaction? In the June 2009 version of their paper entitled "Myopic Extrapolation, Price Momentum, and Price Reversal", Long Chen, Claudia Moise and Xinlei Zhao compare expected and actual momentum returns and explore the detailed relationship between momentum/reversal returns and firm fundamentals. Using monthly stock return data and associated fundamentals for a broad sample of firms spanning 1985-2006, *they conclude that:*

- There is a pattern from short-term momentum to long-term reversal in firm fundamentals that roughly matches observed stock price momentum and reversal. Past winners experience more positive earnings shocks than past losers temporarily during the six to nine months after sorting, when momentum profits peak. After nine months, winners persistently experience more negative earnings shocks than losers.
- Analysts tend to revise both near-term and long-term earnings and cash flow forecasts following this same pattern, reacting to contemporaneous earnings shocks and ignoring predictable long-term earnings reversion.
- Investors likewise drive prices of past winners (losers) up (down) temporarily and then down (up) over the long term. (See the first chart below.)
- After accounting for predictable long-term reversion, past winners actually have significantly lower expected returns than past losers. Momentum pricing is therefore an "error" derived from myopic overweighting of contemporaneous earnings. (See the second chart below.)
- Institutional investors tend to time their holdings well to with respect to near-term momentum and long-term reversal. Individual investors do not, thereby transferring wealth to institutional investors.

The following chart, taken from the paper, plots the cumulative excess return over the Loser Portfolio (bottom fifth) for each of four other portfolios during the 36 months after portfolio formation (time 0). Ranking of the the five portfolios at time 0 is based on past returns from month -12 through month -2 (followed by a skip month). Cumulative excess returns peak at six to nine months and increase systematically with past returns. Excess returns then decline steadily, turning negative for Winner minus Loser at about 18 months. After 36 months, excess returns reach -8% to -10% for all four cases.



The next chart, also from the paper, compares percentage year-over-year quarterly sales growth and operating cost growth (before depreciation) for the Winner and Loser portfolios from 12 months before to 36 months after portfolio formation (time 0). For the year before portfolio formation, the growth rate in sales is greater (less) than the growth rate of operating costs for past winners (losers). These conditions persist for about two quarters after portfolio formation, at which point the sales growth-operating cost growth relationships reverse for both past winners and past losers. In other words, profitability of past winners (losers) increases (decreases) for about six months after portfolio formation and then decreases (increases) for many months thereafter.



In summary, *evidence indicates that investors and analysts tend to extrapolate current earnings shocks and discount their predictable reversion. This shortsightedness manifests as the momentum effect, reflected in both stock prices and analyst cash flow forecasts.*

Originally published at http://www.cxoadvisory.com/2191/momentum-investing/momentum-a-big-mistake/ on July 7, 2009.

Combining Momentum and Moving Averages for Asset Classes

May 12, 2009

A reader wondered about the value of combining momentum and simple moving average signals for asset class allocation, as follows:

- Each month calculate the average momentum of each asset class over the prior 3, 6 and 12 months
- Hold the top positions as long as they are also trading above their 10-month SMA (otherwise go to cash)

We test these rules using exchange-traded funds (ETF) as easily tradable asset class proxies. However, many ETFs have very short histories, greatly restricting any such test. We use S&P Depository Receipts (SPY), iShares Barclays 20+ Year Treasury Bond (TLT) and iShares Russell 2000 Index (IWM) as available asset classes, with historical data limited to July 2002 (by TLT). We use the 13-week Treasury bill (T-bill) yield as a proxy for the return on cash. Each month, we allocate funds to the one asset class with the highest average momentum over the prior 3, 6 and 12 months, unless the momentum leader is below its lagged 10-month SMA, in which case we put all funds into T-bills. Using monthly values for SPY, TLT, IWM and the T-bill yield over the period July 2002 through April 2009 (82 months), *we find that:*

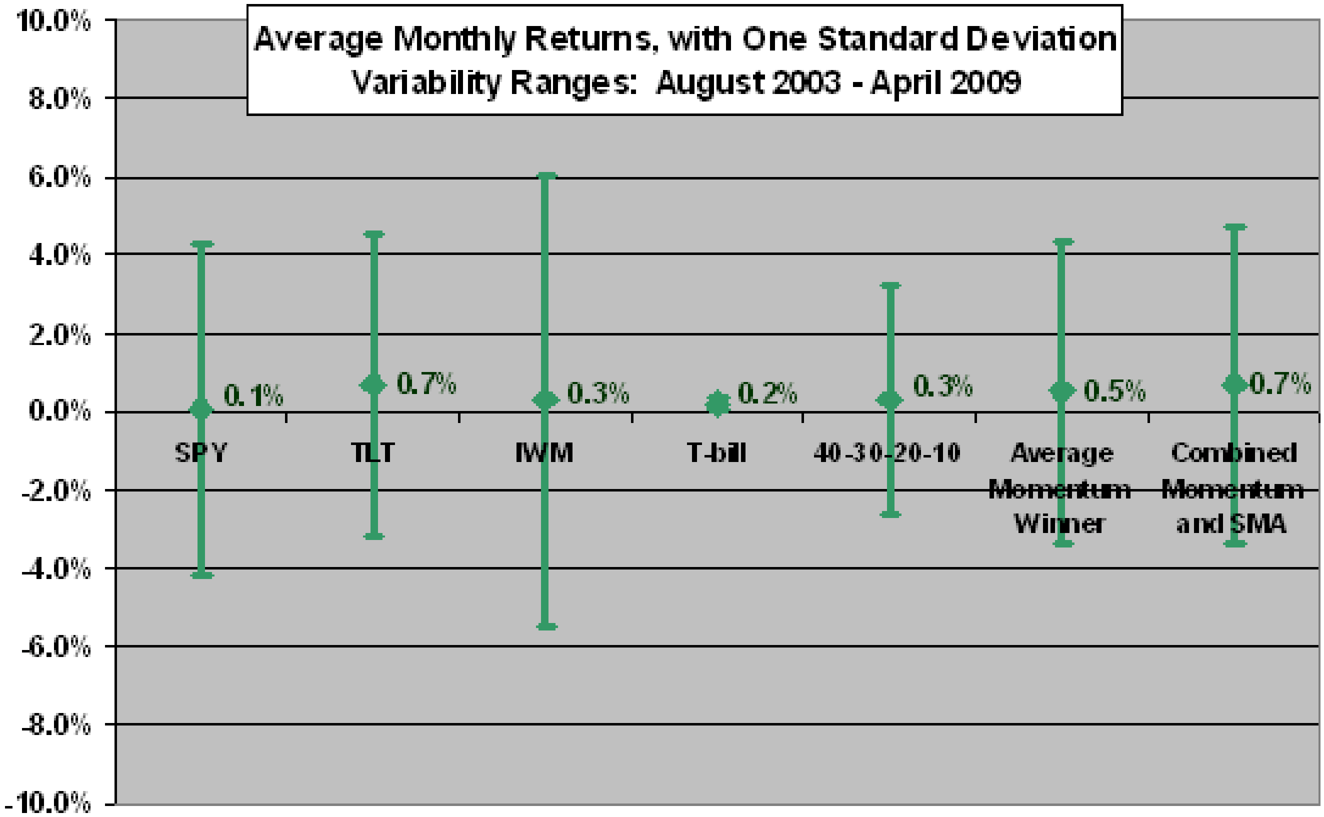
The following chart summarizes average monthly returns and variabilities for seven cases over the period August 2003 through April 2009, as follows:

- Buy and hold SPY.
- Buy and hold TLT.
- Buy and hold IWM.
- Hold T-bills continuously.
- Allocate 40%-30%-20%-10% to SPY-TLT-IWM-Cash, rebalancing monthly at the close (40-30-20-10).
- Allocate all funds monthly at the close to SPY, TLT or IWM based on the highest lagged average momentum (Average Momentum Winner).
- Allocate all funds monthly at the close to SPY, TLT or IWM based on the highest lagged average momentum, unless the momentum winner is below its 10-month SMA, in which case all funds go to T-bills (Combined Momentum and SMA).

The start date of August 2003 is based on calculation of 12-month lagged momentum starting in July 2002.

The winners based on average monthly return are buy-and-hold TLT and Combined Momentum and SMA. Their standard deviations of monthly returns are close, but that of Combined Momentum and SMA is slightly higher (and also slightly higher than that for Average Momentum Winner). The Combined Momentum and SMA approach substitutes T-bills for the momentum winner in only three of 69 months.

The fixed 40-30-20-10 asset allocation approach offers the lowest portfolio variability.



This sample period is very short for evaluating asset class allocation strategies. Testing across multiple business (interest rate) cycles is desirable.

Including more asset classes may well improve the performance of all three of the above asset allocation approaches. Holding multiple asset class momentum winners (rather than just one winner) from a larger selection may hurt or help average returns, depending on how often momentum winners are below their 10-month SMAs and therefore default to cash.

Other combinations of rules are possible. Testing different cases across the same data introduces some data snooping bias in results.

In summary, *a very limited test suggests that adding simple moving average signals to asset class momentum investing may enhance returns.*

Originally published at http://www.cxoadvisory.com/4000/technical-trading/combining-

momentum-and-moving-averages-for-asset-classes/ on May 12, 2009.

A Few Notes on The Ivy Portfolio: How to Invest Like the Top Endowments and Avoid Bear Markets

March 30, 2009

In their 2009 book, *The Ivy Portfolio: How to Invest Like the Top Endowments and Avoid Bear Markets*, Mebane Faber and Eric Richardson "profile the top endowments and then examine how an investor can hope to replicate their returns while avoiding bear markets. The focus [is] on practical applications that an investor can implement immediately to take control of their investment portfolio." Mebane Faber "is the portfolio manager at Cambria Investment Management where he manages equity and global tactical asset allocation portfolios" and a co-founder of AlphaClone, an investing research web site. Eric Richardson is Chairman and founder of Cambria Investment Management. The book has a complementary web site that links to source materials. The *principal messages of the book are:*

Chapters 1-3: The top-performing university endowments (Yale and Harvard) are worthy of emulation by individual investors. These endowments have excelled through active management of portfolios diversified per Modern Portfolio Theory across a wide variety of asset classes (U.S. stocks, foreign stocks, bonds, cash, real assets, private equity and hedge funds), with disciplined rebalancing toward "Policy Portfolio" weightings that tilt toward equity-like assets. Active management means selecting the best assets within class either directly or indirectly by selecting the best asset managers.

Chapter 4-6: Individual investors can on their own easily emulate parts of the endowment portfolios with a simple Policy Portfolio comprised of low-cost exchange traded funds (ETF) designed to mimic the returns of relevant asset classes, rebalanced annually. This easy emulation does not include: (1) private equity and hedge funds; and, (2) active selection of specific assets within class. Disciplined rebalancing toward Policy Portfolio weightings is important to performance.

Chapter 7-8: Individual investors can easily enhance this simple endowment emulation, as follows:

> Exploit the return momentum effect for each ETF asset class proxy in the Policy Portfolio by allocating policy-dictated funds to the ETF (to cash) when the ETF is above (below) its simple 200-day moving average.
>
> Amplify the momentum effect by rotating all funds monthly to the one, two or three ETF asset class proxies with the highest returns over the past three, six and 12 months (average of the three).

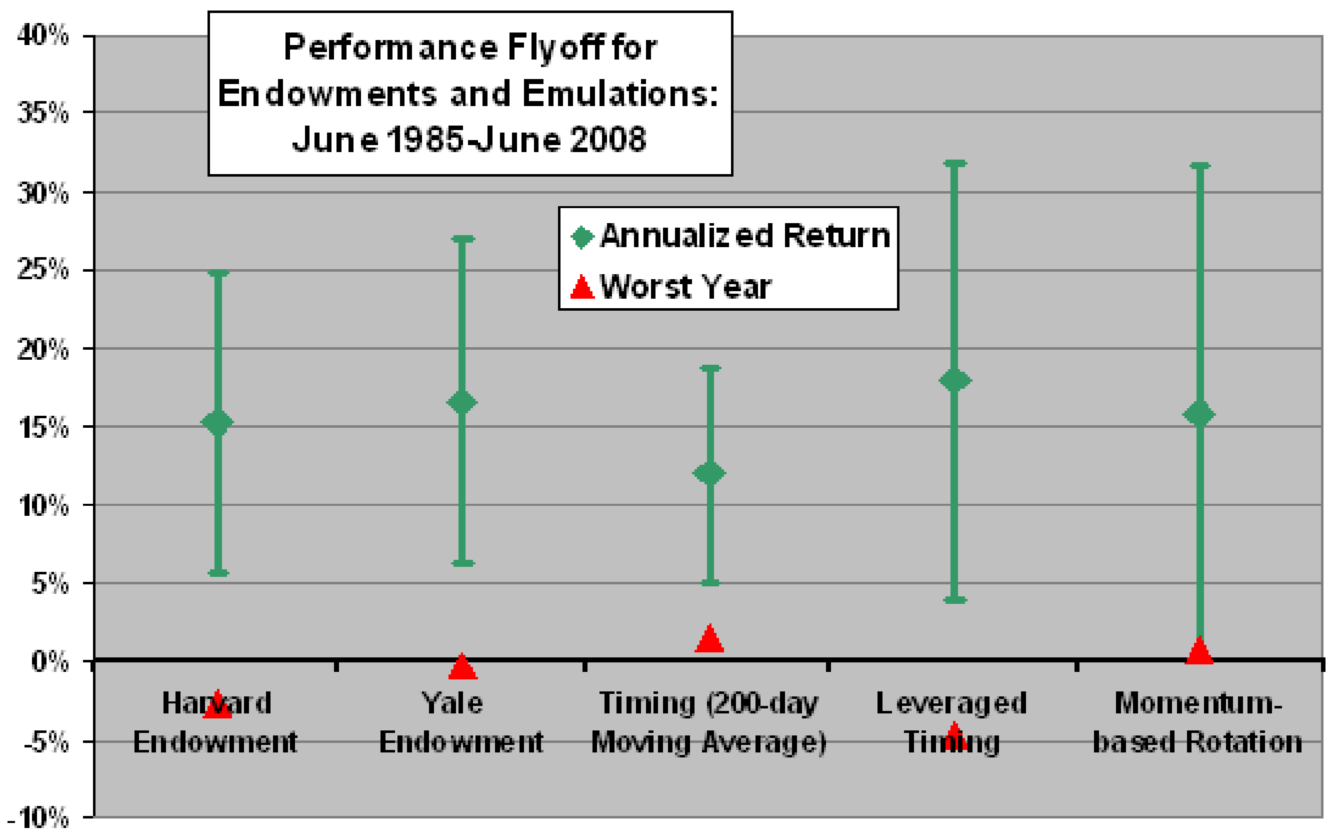
Extend the diversification of the Policy Portfolio by further segmenting asset classes as enabled by available ETFs, allow shorting of asset classes (per the momentum rule) and/or exclude bonds.

If borrowing costs are low, apply leverage.

Actively select specific assets to populate asset classes based on the holdings of top fund managers (such as Bershire Hathaway, Greenlight Capital and Blue Ridge Capital) as reported in quarterly 13F reports to the Securities and Exchange Commission.

The following chart, constructed from data in Table 7.10 in the book, compares the annualized returns for the Harvard and Yale endowments and for three enhancements of the simple endowment emulation over the period June 1985 through June 2008. The variability ranges for each are one standard deviation of annual returns. The chart also shows the worst-year return. Results indicate that the emulation models are competitive with the endowments. However, results for the three enhanced emulation models are "gross returns, so management fees, taxes and commissions would eat into returns a bit."

Note that, over large parts of the period of this analysis, simple and cheap asset class proxies (such as ETFs) were not available to investors. Also, trading frictions in "the old days" (pre-decimalization, pre-discount broker, olden days mutual funds) were higher than now. Costs of constructing and maintaining the three enhanced emulation models during these subperiods may have eaten into emulation returns more than "a bit." Small accounts may not have been practically able to achieve the desired level of diversification.



Two other considerations may affect future performance of the enhanced emulation models:

> With asset class diversification, rebalancing and timing greatly simplified through proliferation of ETFs, the adaptive marketplace might permanently degrade the models by disrupting old long-run correlations and timing premiums. (The extreme stress test would be the “if everyone does this” case.)
>
> Much of the logic in the book (like Modern Portfolio Theory) assumes the normality, or at least statistical tractability, of financial market returns via mean, standard deviation and Sharpe ratio metrics. Actual return distributions may in fact be too wild to rely on these metrics, with the stress tests considered in the book (such as “Worst Year” during June 1985-June 2008) not “wild” enough to realize a breakdown.

In summary, *The Ivy Portfolio offers investors a well-reasoned, well-documented, easily understood and easily implemented approach to long-term, self-directed portfolio management based on disciplined asset class diversification enhanced by momentum. While investors should expect to underperform the modeled level of returns, the approach has considerable support from formal research.*

Originally published at http://www.cxoadvisory.com/2694/technical-trading/a-few-notes-on-the-ivy-portfolio-how-to-invest-like-the-top-endowments-and-avoid-bear-markets/ on March 30, 2009.

Combining Value and Momentum Across Asset Classes

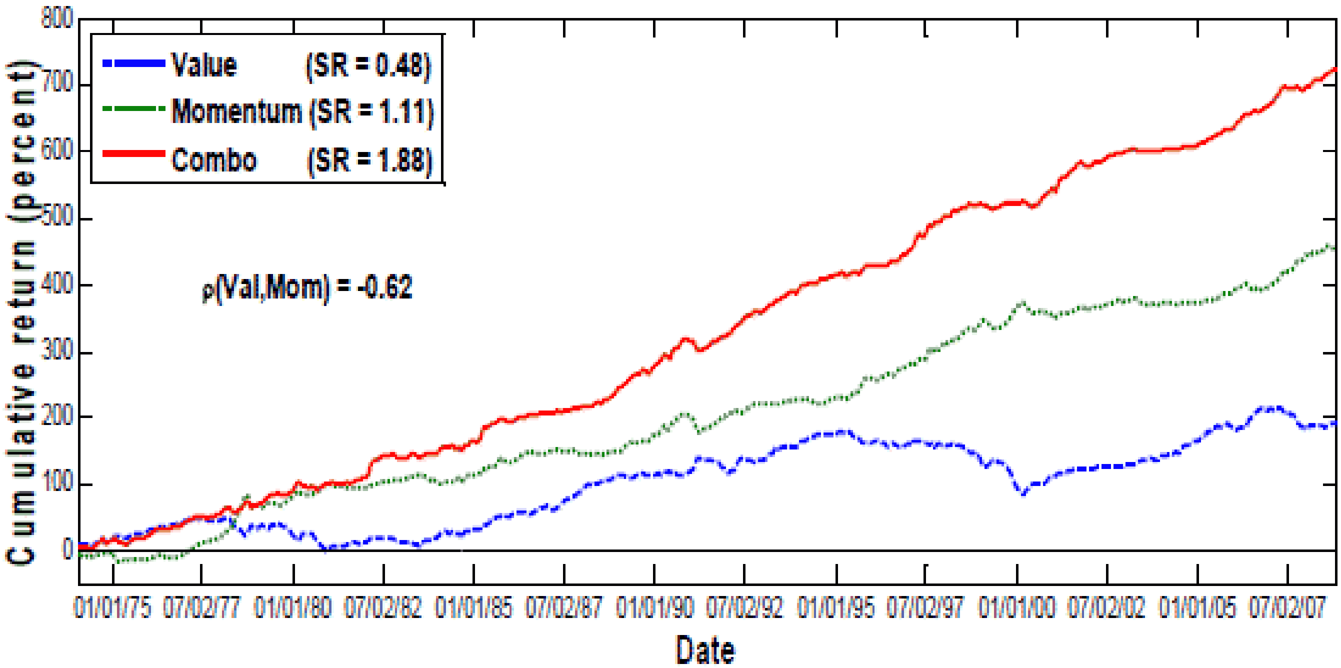
March 27, 2009

The value premium and the momentum effect are arguably complementary drivers of financial asset pricing dynamics, with the latter alternatively creating and extinguishing the former. Does empirical evidence support this view across asset classes? In the February 2009 version of their paper entitled "Value and Momentum Everywhere", Clifford Asness, Tobias Moskowitz, and Lasse Pedersen investigate the interplay of value and momentum across asset classes worldwide, as follows: (1) stocks within four major countries; (2) country equity indexes; (3) government bonds; (4) currencies; and, (5) commodities. They calculate momentum based on return over the past 12 months, excluding the most recent month, for all asset classes. They estimate value based on measures commonly used for each asset class (such as book-to-market ratio for stocks). Using price and value characteristics data for broad samples of these asset classes, *they conclude that:*

- Value and momentum both deliver positive abnormal returns across markets and asset classes.
- Value (momentum) in one asset class relates positively to value (momentum) in other asset classes, and value relates negatively to momentum both within and across asset classes.
- The negative correlation between value and momentum returns gives a simple equal-weighted combination of the two a much higher Sharpe ratio and more stability across markets and time periods than either value or momentum alone (see the chart below). In every region, the value-momentum combination exhibits less than half the volatility of either value or momentum.
- A combined value-momentum strategy implemented across all asset classes enhances risk-adjusted returns compared to the same strategy implemented for individual or subgroups of asset classes.
- Over time, value and momentum strategies become less profitable, more positively correlated across markets/asset classes and less negatively correlated with each other.
- Macroeconomic indicators explain very little of the variation in value and momentum returns and return correlations.
- Increasingly over time, value (momentum) strategies weaken (strengthen) when liquidity is poor/declining. A combination of value and momentum in each market therefore provides good diversification against aggregate liquidity risk.
- During extreme events, a more negative correlation between value and momentum returns tends to offset a loss of diversification due to increased correlations for both value returns and momentum returns across markets.
- The strong, opposing turn-of-the-year patterns documented for value and momentum strategies as applied to US equities are not prevalent across markets or asset classes.

The following chart, taken from the paper, compares cumulative returns and annualized Sharpe ratios (SR) for a value strategy, a momentum strategy and a 50-50 value-momentum strategy (rebalanced monthly) as applied to an equal-weighted combination of stock selections from the US, UK, Japan and continental Europe. The benefit of combining the two negatively correlated (-0.62) value and momentum strategies is evident.

The Sharpe ratio for a 50-50 value-momentum strategy limited to US stocks is 1.13, compared to 1.88 as diversified across the four equity markets.



In summary, *a portfolio that combines value and momentum strategies across global equity markets and other asset classes may offer investors relatively high returns with low volatility.*

Originally published at http://www.cxoadvisory.com/2091/value-premium/combining-value-and-momentum-across-asset-classes/ on March 27, 2009.

The NoLoad FundX Mutual Fund Momentum Approach

February 10, 2009

A reader offered:

> "I suggest you test the performance of NoLoad FundX, a newsletter often cited as a violation of the Efficient Market Hypothesis. They offer decent data for an analysis. You can also use their mutual fund, FundX Upgrader (FUNDX), for 2008 performance."

The NoLoad FundX approach is essentially momentum-based (with funds rather than stocks), as follows: "Upgrading involves measuring near-term performance of mutual funds (twelve months and less) and comparing them to returns of other funds with similar risk. We invest in funds with the best recent returns, and hold them as long as they continue to outperform. When a fund drops in our ranks, we 'Upgrade' to the new market leaders." Using results of relevant research, the performance data presented by NoLoad FundX and actual performance data for the FUNDX mutual fund, *we conclude that:*

There is evidence to support a belief in the efficacy of applying a medium-term momentum strategy to funds. In aggregate, this evidence suggests that exploiting fund-based momentum may depend critically on: (1) limiting the universe of funds considered to those focused on specific asset classes and styles; (2) concentrating investment in a very few of the best-performing of these focused funds at any one time; and, (3) fairly frequent reallocation as old winners fade and new ones emerge.

There is also research that measures mutual fund performance persistence for fixed holding periods based on past performance. This research, somewhat less connected to the NoLoad FundX approach than that listed above, generally concludes that mutual fund performance persistence over periods of one to a few years exists more reliably for past losers than past winners.

The performance results presented at "Performance of Upgrading Monthly to the Top Five Funds" indicates a fund momentum effect, outperforming the S&P 500 index in 20 of 28 years (underperforming during five-year and three-year losing streaks). However, these results may not realistically incorporate all the frictions of actual fund-switching, whether for traditional mutual funds or for exchange-traded funds (ETF). In fact, NoLoad FundX amends these results with the statement: "Although fund-imposed redemption fees are factored into the results, brokerage fees, taxes and any outside management fees…are not. If applicable, these additional costs would have a negative impact on one's actual returns."

For a current view of the performance potential of the NoLoad FundX strategy, with trading frictions, we compare the total return performance of the FUNDX mutual fund over its entire available history (since November 2001) with those of five ETFs:

- DIAMONDS Trust, Series 1 (DIA) – very large capitalization U.S. equities.
- iShares Russell Midcap Index (IWR) – mid-capitalization U.S. equities
- iShares Russell 2000 Index (IWM) – small capitalization U.S. equities.
- iShares Barclays 7-10 Year Treasury (IEF) – mid-term U.S. Treasury notes (available only since July 2002).
- SPDR Gold Shares (GLD) – gold (available only since November 2004).

As of 1/31/09, FUNDX has positions in DIA, IWM and GLD (among a total of 41 positions).

The following table summarizes total returns (using adjusted closing prices for the ETFs) for seven investing horizons since the inception of FUNDX at the beginning of November 2001. Some observations are:

FUNDX matches or beats returns of all three equity ETFs for three of the seven investment horizons.

FUNDX substantially underperforms the bond and gold ETFs for all horizons available for comparison. The point is not that investors should benchmark FUNDX against bond or gold returns (although, as noted, FUNDX holds GLD as of 1/31/09, and gold probably should be factored into any bencmark for the fund), but that a momentum strategy that excludes or arbitrarily segments asset classes may not be optimal.

For taxable accounts, taxes would likely degrade the FUNDX performance relative to buy-and-hold returns of the ETFs substantially due to FUNDX trading of funds (“upgrading”).

Total Return	FUNDX	DIA	IWR	IWM	IEF	GLD
1-Month	-7.4%	-8.3%	-7.1%	-9.7%	-3.9%	5.5%
3-Month	-12.8%	-13.9%	-13.5%	-16.6%	8.9%	28.0%
6-Month	-37.3%	-28.7%	-39.7%	-37.0%	9.1%	1.4%
12-Month	-41.2%	-34.9%	-42.1%	-36.7%	7.9%	-0.1%
3-Year Annualized	-11.9%	-7.6%	-15.2%	-14.1%	8.2%	17.2%
5-Year Annualized	-1.4%	-3.2%	-3.1%	-4.1%	5.9%	NA
Cumulative from (11/1/01)	16.4%	2.6%	16.4%	13.4%	NA	NA

These real results, in the context of the strong hypothetical intermediate-term momentum results presented for the NoLoad FundX approach, indicate that the FUNDX mutual fund implementation of the approach may not substantially exploit available momentum. Possible reasons for this ostensible underachievement are:

- The fees, expenses and other frictions involved in implementing FUNDX substantially offset momentum returns (the market is mostly efficient after frictions).
- FUNDX does not sufficiently concentrate positions among just a very few funds with the highest momentum.
- FUNDX does not reallocate frequently enough to those funds with the very highest levels of momentum.

In addition, the NoLoad FundX approach might benefit from consolidating a wide enough range of asset classes (for example, to include bond funds) within a single analysis universe.

In summary, *while research generally supports belief in an intermediate-term momentum effect for equities, it is not obvious that the FUNDX mutual fund substantially exploits the effect. Investors may be able to capture more of the effect by applying the NoLoad FundX approach more purely themselves.*

For another perspective on NoLoad FundX, see Mark Hulbert's 2006 article entitled "What Constitutes the Long Term?", which addresses the streakiness of the performance of this strategy.

Originally published at http://www.cxoadvisory.com/2689/mutual-hedge-funds/the-noload-fundx-mutual-fund-momentum-approach/ on February 10, 2009.

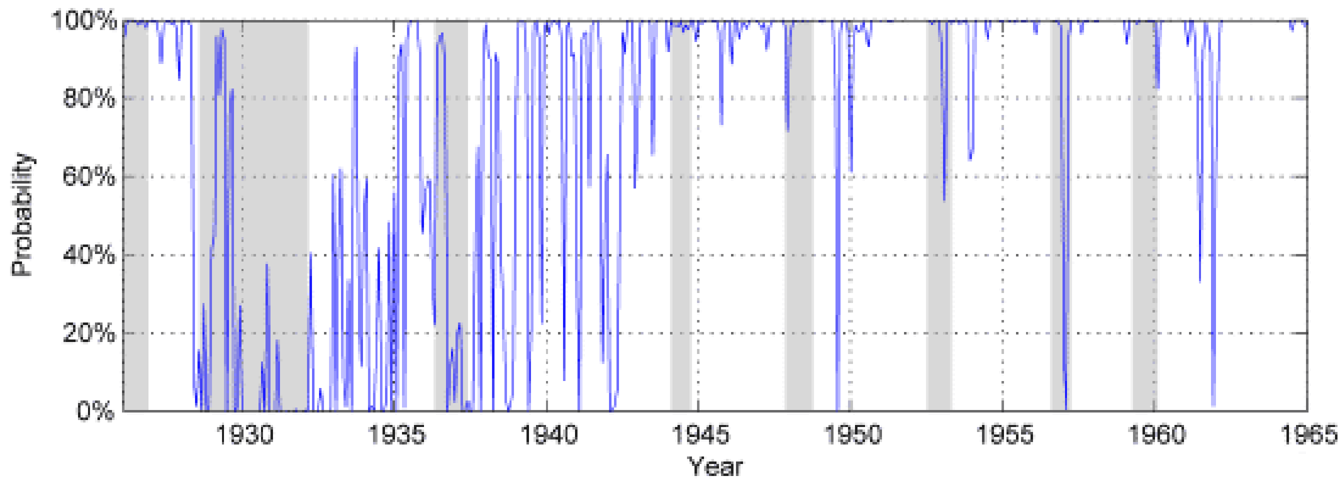
Four Factors and Two Regimes

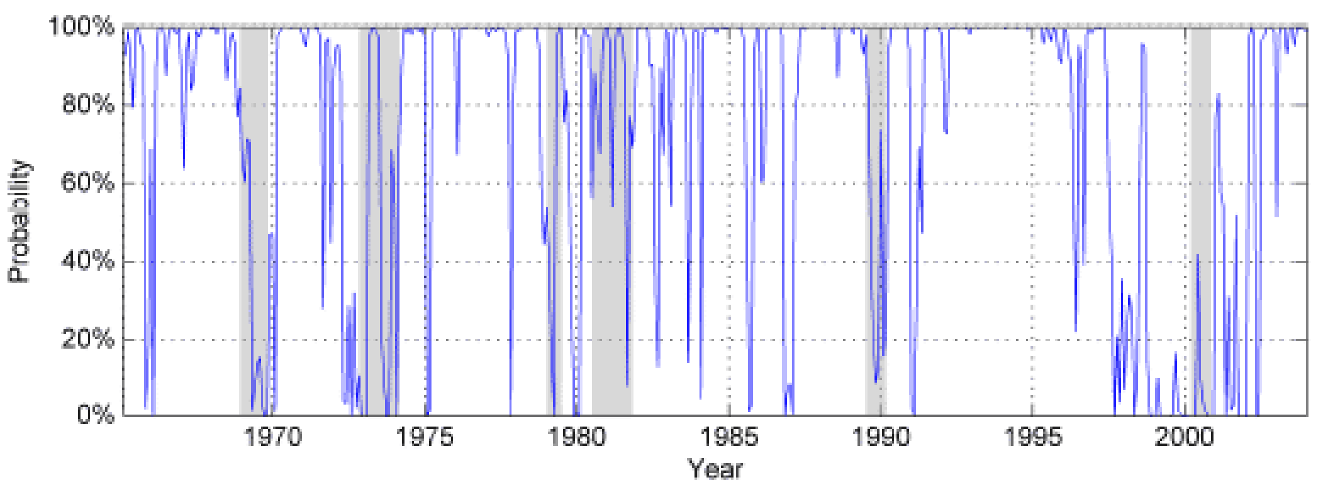
January 28, 2009

Do returns associated with the four famous factors (market, size, book-to-market, momentum) vary systematically with the state of the market (such as bull or bear)? In their January 2009 paper entitled "The Effect of Market Regimes on Style Allocation", Manuel Ammann and Michael Verhofen investigate how returns for the four factors differ between market states as determined by a multivariate two-state model of the overall equity market. Using U.S. stock market and factor data spanning 1927-2004, *they conclude that:*

- There are two reasonably distinct overall equity market regimes with different mean returns and volatilities: low-volatility and high-volatility. Market volatility is 2.6 times higher for the latter regime than for the former.
- The low-volatility regime, occurring about three quarters of the time, relates to high annual returns for the overall equity market (10.2%) and momentum stocks (12.4%), and low annual returns for small capitalization stocks (1.9%) and value stocks (2.6%).
- The high-volatility regime, occurring about one quarter of the time, relates to low annual returns for the overall equity market (0.4%), momentum stocks (-1.3%) and small capitalization stocks (3.1%) and high annual returns for value stocks (15.2%).
- An out-of-sample backtest indicates that switching styles according to market regime can be profitable. Specifically, momentum investing during the low-volatility regime and value investing during the high-volatility regime outperforms consistently and to a degree that appears profitable after accounting for transaction costs.

The following chart, taken from the paper, shows the modeled probability of the U.S. stock market being in the low-volatility regime during 1927-2004, with shaded areas corresponding to National Bureau of Economic Research recessions. The probability of being in the low-volatility regime is about 75% over the entire sample period. However, this probability rises (falls) to about 80% (55%) during economic expansions (recessions). The low-volatility regime favors momentum investing, while the complementary high-volatility regime favors value investing.





It seems reasonable to assume that the U.S. equity market is currently in the high-volatility regime.

In summary, *equity investors may want to alternate between momentum and value investing styles as the overall stock market varies from low-volatility to high-volatility states.*

Originally published at http://www.cxoadvisory.com/156/big-ideas/four-factors-and-two-regimes/ on January 28, 2009.

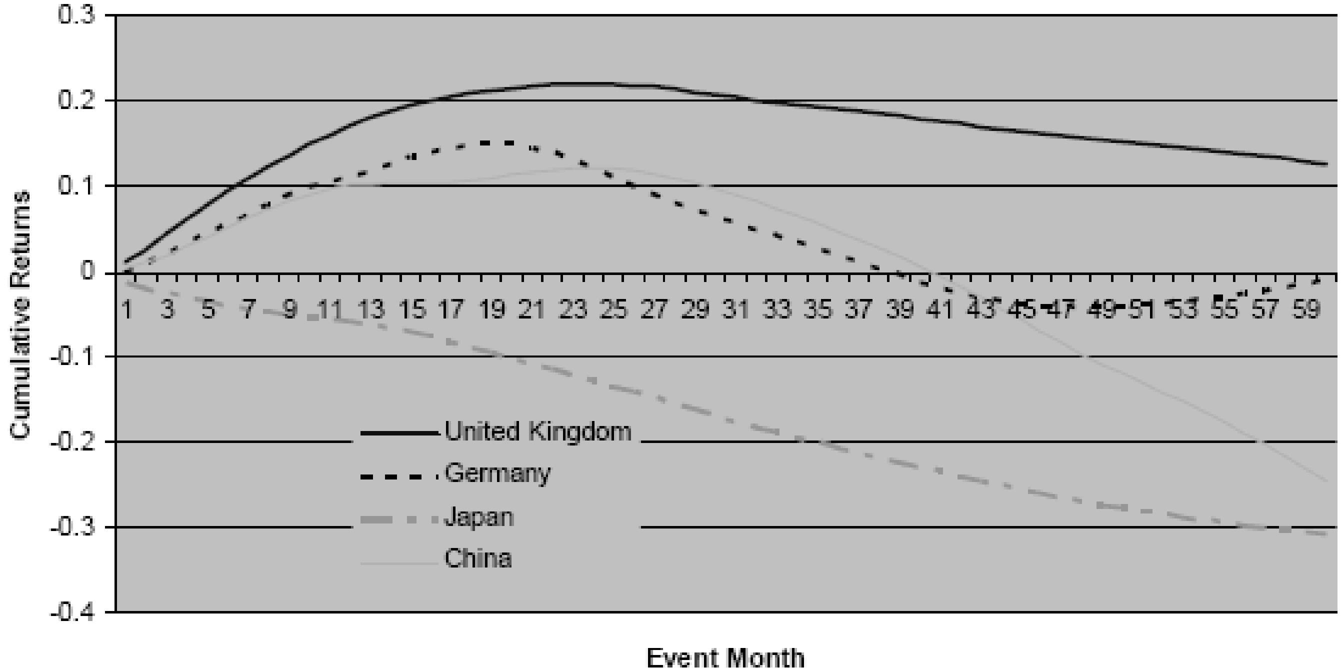
International Test of Momentum Strategies

January 22, 2009

Do momentum trading strategies work consistently across country markets? In his December 2008 paper entitled "Are Anomalies Still Anomalous? An Examination of Momentum Strategies in Four Financial Markets ", Daxue Wang applies various tests to measure the profitability of momentum strategies in the two largest stock markets in each of Europe (UK and Germany) and Asia (Japan and China). He tests overlapping equally weighted portfolios formed on returns over the past 3, 6, 9 or 12 months (no wait month) and held for 3, 6, 9 or 12 months. Using monthly stock price data and firm characteristics for companies comprising more than 95% of market capitalization in each country over the period 1990 (1994 for China) through 2006, *he concludes that:*

- Equity markets in the United Kingdom and Germany exhibit medium-term momentum for nearly all holding periods over the entire sample period and over subperiods, while Japan shows a medium-term return reversal for nearly all holding periods. China shows evidence of medium-term momentum for many holding periods.
- Specifically, monthly returns for the 16 equally weighted winner-minus-loser (top 10% minus bottom 10%) momentum strategies over the entire sample period range from:
  - +0.19% to +1.75% per month in the UK, with 15 of 16 significantly positive.
  - +0.53% to +1.24% per month in Germany, with 14 of 16 significantly positive.
  - -0.02% to +1.11% per month in China, with 10 of 16 significantly positive.
  - -0.71% to -0.02% per month in Japan, with 0 of 16 significantly positive and 9 of 16 significantly negative.
- For many strategies, momentum profits are significant after incorporating reasonable trading frictions.
- Like the U.S. market, momentum profits reverse for holding periods longer than about two years (see the chart below).
- Unlike the U.S. market, there is no January effect (temporary reversal) for momentum.
- The Fama-French three-factor model (market, size, book-to-market) does not explain momentum profits for most strategies.

The following chart, taken from the paper, compares the cumulative returns for equally weighted winner-minus-loser (top 10% minus bottom 10%) momentum portfolios in the UK, Germany, Japan and China formed on returns over the past six months and held for five years. Stocks included comprise over 95% of total market capitalization in each country. The graph for China is very faint, tracking close to that for Germany over the first four years. Cumulative returns for the UK, Germany and China peak after 18-24 months, with China exhibiting the most dramatic subsequent reversal. Japan shows an immediate and persistent reversal of past returns.



In summary, *medium-term momentum investing may be profitable in most, but not all, international equity markets.*

Originally published at http://www.cxoadvisory.com/1985/momentum-investing/international-test-of-momentum-strategies/ on January 22, 2009.

Time for Momentum ETFs?

December 4, 2008

Why are there no "momentum" exchange-traded funds (ETF)? What would it take to create them? How might they have performed in recent years? In their November 2008 paper entitled "Momentum and Contrarian Stock-Market Indices", Jon Eggins and Robert Hill propose a new class of diversified momentum (overweighting stocks that have recently outperformed) and contrarian (underweighting these same stocks) ETFs derived from partitions of a benchmark index. Their methodology allows adjustment of the degree to which a partition is momentum or contrarian via a single parameter, with associated turnover increasing as the degree of momentumness or contrarianness increases. ETFs based on such index partitions would allow individual investors practical access to diversified momentum/contrarian strategies and provide performance benchmarks for momentum and contrarian investment managers. Using price data for the components of the Russell 1000 index over the period June 1995-June 2007 to construct baseline momentum and contrarian indexes, *they conclude that:*

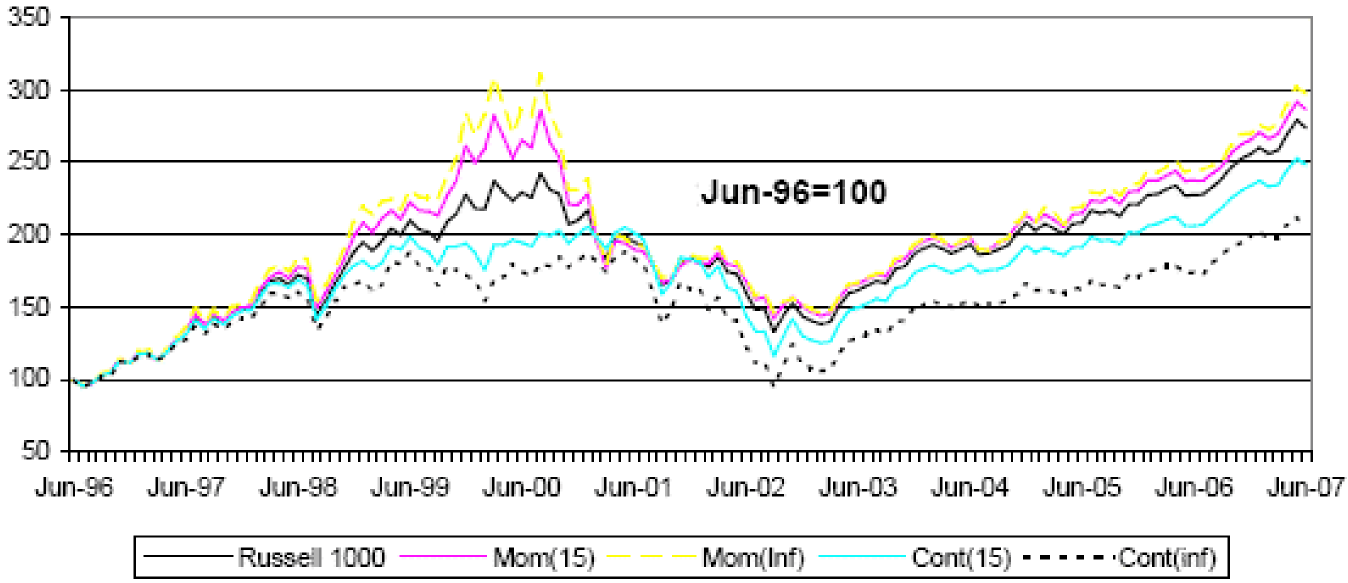
- Over the entire sample period, short-term momentum and long-term contrarian indexes outperform the reference Russell 1000 index.
- The momentum and contrarian indexes have higher turnovers than does the Russell 1000 index, but a long-only fund sponsor could control turnover to a manageable level while maintaining distinctive momentum and contrarian styles.
- Momentum/contrarian strategies are not simply proxies for growth/value indexes.
  - During the "tech" boom, there is high affinity between momentum and growth indexes, and between contrarian and value indexes. These relationships reverse after 2001. Most recently, the relationships disappear.
  - Momentum and contrarian indexes generate higher turnover than value and growth indexes (but lower turnover than long-short momentum strategies and many mutual funds).

The following chart, taken from the paper, compares the cumulative performance from June 1996 to June 2007 of the Russell 1000 index and four 12-month formation period, 12-month holding period (12,12) momentum and contrarian indexes derived from it, as follows:

1. A (12,12) momentum index with degree of momentumness corresponding to about 23% annual turnover [Mom(15)].
2. A (12,12) momentum index with degree of momentumness set to maximum, with annual turnover around 40% [Mom(inf)].
3. A (12,12) contrarian index with degree of contrarianness corresponding to about 25% annual turnover [Cont(15)].
4. A (12,12) contrarian index with degree of contrarianness set to maximum, with annual turnover around 50% [Cont(inf)].

In general, momentum strategies outperform contrarian strategies for a 12-month holding period, and the momentum-contrarian divergence increases with the degree of index momentumness/contrarianness. Moreover, for a 12-month holding period, momentum (contrarian) strategies tend to outperform (underperform) the reference Russell 1000 index. Contrarians must hold for much longer periods to exploit eventual reversal.

Note that these index performance calculations do not include trading frictions, which might eliminate the outperformance of momentum indexes relative to the Russell 1000.



In summary, *momentum and contrarian ETFs based on long-only partitions of broader indexes might offer individual investors practical and diversified access to the momentum factor, and to the associated longer-term contrarian reversal.*

Originally published at http://www.cxoadvisory.com/1949/momentum-investing/time-for-momentum-etfs/ on December 4, 2008.

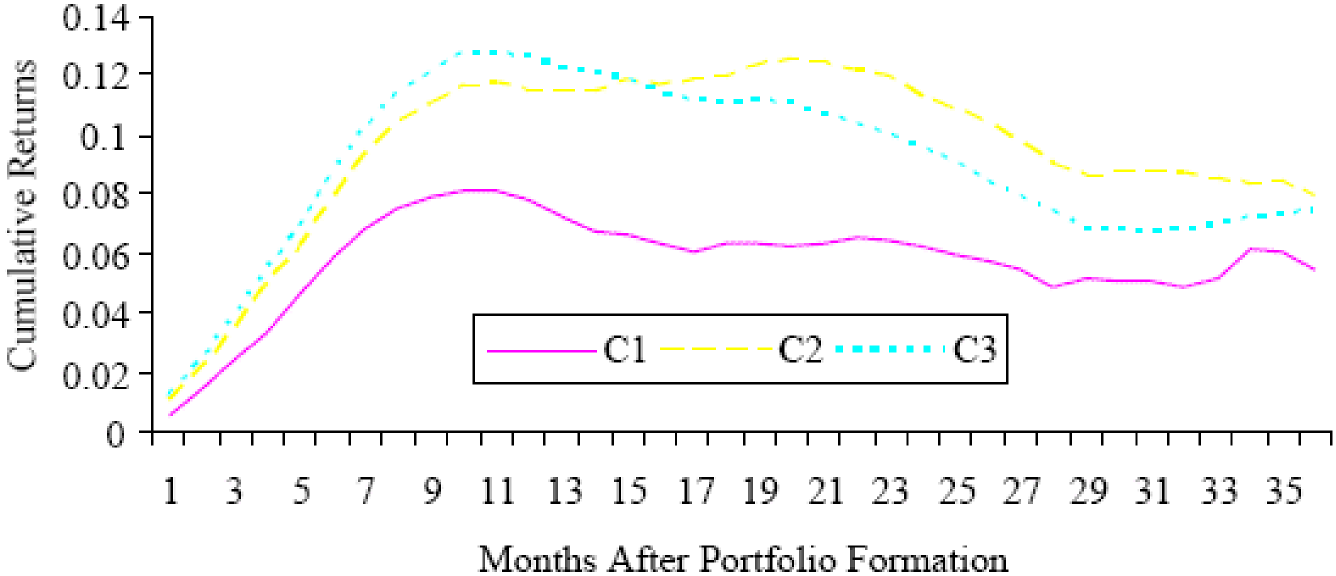
Enhancing Momentum Returns with Style

September 2, 2008

Do growth and value investing styles have momentum? If so, can investors/traders enhance momentum trading returns by accounting for the stylishness of stocks (the degree to which they fit into either a growth or value style)? In their August 2008 paper entitled "Style Investing, Co-movement and Return Predictability", Sunil Wahal and Deniz Yavuz measure returns from the combination of stock momentum and stock stylishness. They consider momentum portfolio formation and holding intervals of three, six and 12 months, with an intervening skipped month. They define stock stylishness (but do not use that term) as the degree of stock price co-movement with either growth stocks or value stocks over the past three months. Using monthly returns, book-to-market ratios and market capitalizations for a broad set of stocks over the period 1965-2006, *they conclude that:*

- High-stylishness, past winner (loser) portfolios consistently and significantly outperform low-stylishness, past winner (loser) portfolios using both raw returns and risk-adjusted (market, size, book-to-market) returns.
- For six-month momentum portfolio formation and holding intervals over the 1999-2006 subperiod, the average raw (risk-adjusted) return increases from 0.86% (1.08%) per month for the least stylish third of stocks to 1.28% (1.50%) percent for the most stylish.
- Long-horizon (more than a year) reversals are also larger for high-stylishness portfolios.
- Results generally hold for: equal-weighted and value-weighted portfolios; raw and risk-adjusted returns; and, major subperiods.

The following chart, taken from the paper, compares average cumulative returns for different levels of stylishness over the 36 months after formation of equal-weighted hedge portfolios based on past six-month momentum (top 10% minus bottom 10%) during 1965-2006. Portfolio C1/C2/C3 contains stocks in the bottom/middle/top third of stylishness, as indicated by the degree to which stock price moves with either growth stocks or value stocks over the prior three months. The chart shows that stylishness substantially augments momentum returns during the first year after portfolio formation. Also, return reversal during the second year after portfolio formation is larger for high-stylishness stocks.



In summary, *investors/traders may be able to enhance momentum trading strategies by focusing on stocks that fit most strongly into a growth or value style.*

Originally published at http://www.cxoadvisory.com/1847/value-premium/enhancing-momentum-returns-with-style/ on September 2, 2008.

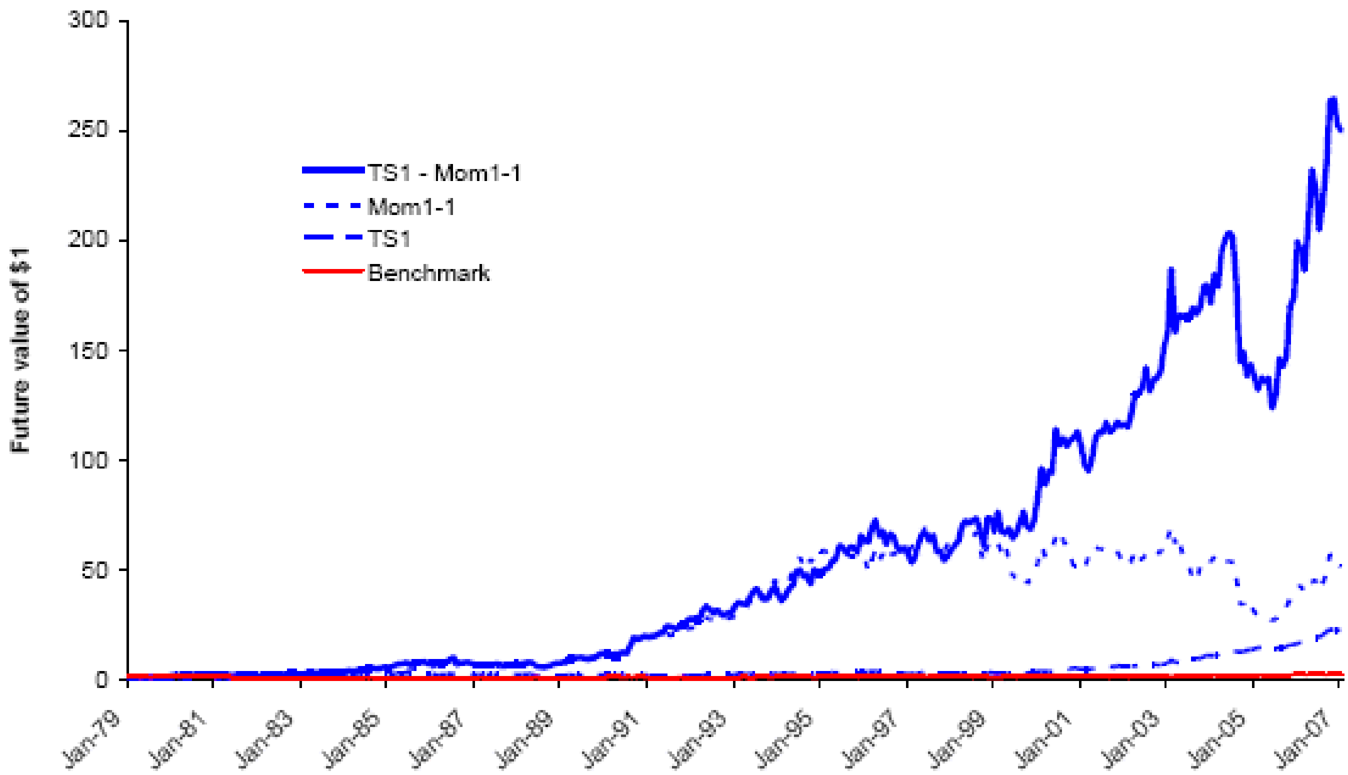
Combining Momentum and Roll Return Signals for Commodity Futures

August 7, 2008

Does combining two commodity futures trading signals shown to be effective in prior research, momentum and roll return (term structure), improve on both? In the May 2008 version of their paper entitled "Tactical Allocation in Commodity Futures Markets: Combining Momentum and Term Structure Signals", Ana-Maria Fuertes, JoÃ«lle Miffre and Georgios Rallis measure the combined value of momentum and roll return signals in the design of commodity futures trading strategies. They test combinations that iteratively buy backwardated (positive roll return) winners and short contangoed (negative roll return) losers. Using daily closing prices on the nearby, second nearby and distant contracts for 37 commodities as available over the period January 1979 through January 2007, *they find that:*

- The momentum (roll return) strategies that are significantly profitable earn an average risk-adjusted annual return of 10.14% (12.66%) before transaction costs, compared to just 2.48% for a passive long-only portfolio that equally weights all 37 commodities.
  - Trend following rules with formation periods of one, three and 12 months and a holding period of one month (Mom1-1, Mom3-1 and Mom12-1) are the best momentum strategies.
  - The best roll return strategy (TS1) buys the 20% of commodities with the most positive roll returns and shorts the 20% with the most negative roll returns each month.
- Double-sort strategies that exploit both momentum (Mom1-1, Mom3-1 or Mom12-1) and roll return (TS1) signals with monthly holding/rebalancing generate an average risk-adjusted annual return of 21.02% before transaction costs. The most profitable double-sort strategy is TS1 combined with Mom1-1 (see the chart below).
- These double-sort strategies involve a small subset of contracts that are liquid and cheap to trade, such that they offer an average risk-adjusted annual return of 20.21% after reasonable transaction costs.
- The abnormal returns of the double-sort strategies are not a result of data mining.
- Returns from the double-sort strategies have very low correlations with those of traditional asset classes and are therefore promising as portfolio diversifiers.

The following chart, taken from the paper, plots the value of a $1.00 initial investment in TS1 – Mom1-1 combined, Mom1-1 only, TS1 only and the passive long-only benchmark over the entire sample period. It illustrates both the strong performance and high risk of the active strategies. The outperformance of the combined TS1 – Mom1-1 strategy appears to be driven by momentum until 1998 and by roll return since.



In summary, *commodity futures trading strategies that combine momentum and roll return may offer strong performance largely uncorrelated with those of stocks and bonds.*

Originally published at http://www.cxoadvisory.com/1817/momentum-investing/combining-momentum-and-roll-return-signals-for-commodity-futures/ on August 7, 2008.

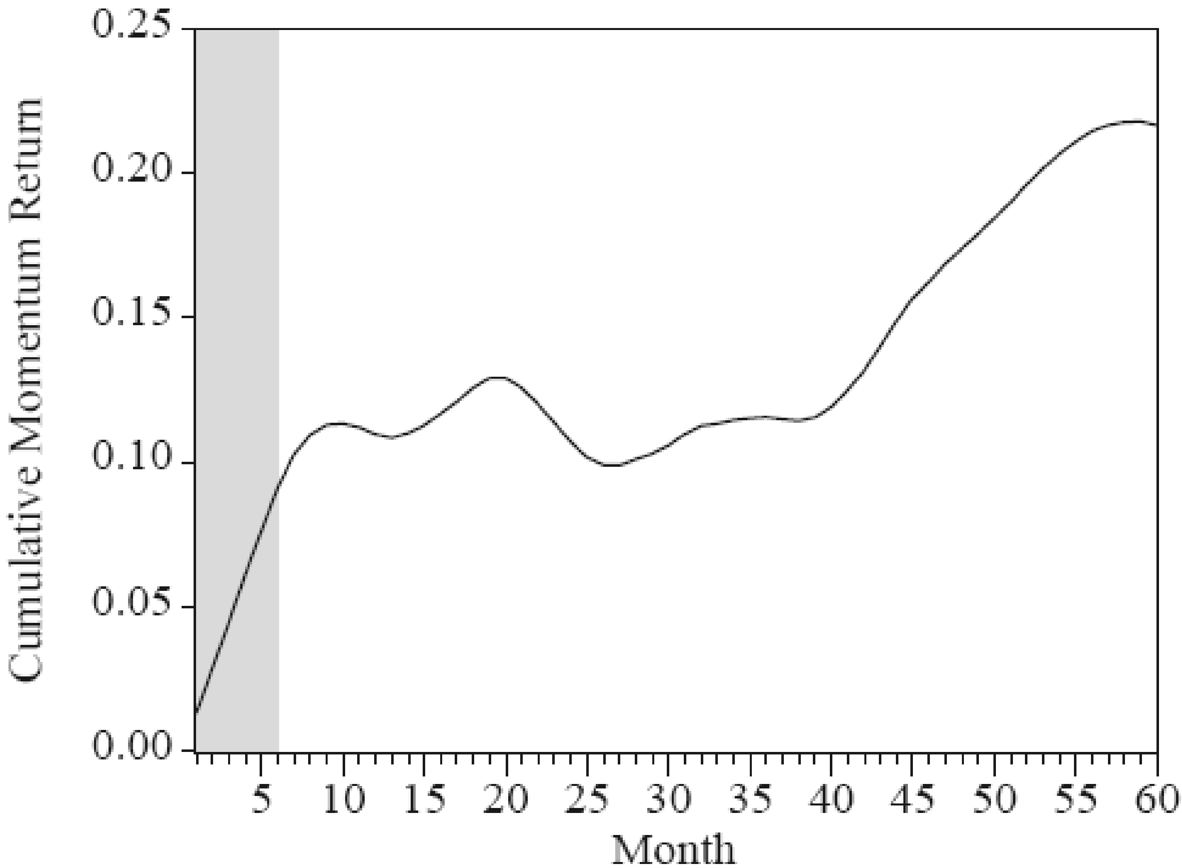
Momentum Returns for Large Caps

July 30, 2008

Are momentum trading strategies reliable and economically significant after trading frictions for large-capitalization stocks? In his November 2006 paper entitled "Alpha Generating Momentum Strategies", Gregor Obrecht test 32 momentum trading strategies on large-capitalization U.S. stocks. The strategies encompass all combinations of: formation periods of three, six, nine and 12 months; wait periods of zero months and one month; and, holding periods of three, six, nine and 12 months. Using monthly returns for S&P 100 stocks over the period 12/85-8/06, *he concludes that:*

- All 32 hedge portfolios that are long (short) the tenth of stocks with the highest (lowest) momentum generate positive alpha before trading frictions. Results for 16 of 32 such portfolios are statistically significant. Use of a one-month wait period appears to be advantageous only for short holding periods.
- Focusing on the strategy using a six-month formation period, zero wait period and six-month holding period:
    - Momentum returns are significant over 12/85-12/94 and 1/95-8/00 subperiods, but they disappear for 9/00-8/06. The most likely explanation for the breakdown is that momentum does not work during bear markets.
    - Among large-capitalization stocks, momentum effects may be strongest in June, July and September.
    - Adjustments for market, size and book-to-market risk factors do not explain momentum returns.
    - Momentum returns are more likely an adjustment to past underreaction than an overreaction to recent events (see chart below).
    - Inclusion of reasonable trading frictions leaves a net alpha of 2.33% over six months (growing to 7.55% for a 10-month holding period).

The following chart, taken from the paper, shows the average cumulative return over 60 months after hedge portfolio formation based on past six-month momentum with no wait period. The shaded area indicates a nominal six-month holding period, which captures most of the abnormal returns available over the first year. Because the cumulative return does not revert toward zero, results suggest that momentum reflects adjustment to past underreaction rather than an overreaction in and of itself. Note that this figure omits the most recent 60 months of data in the sample due to unavailability of returns for the entire cumulative return window.



In summary, *momentum trading strategies generally offer significantly positive alpha for large-capitalization U.S. stocks, but the strategies may not work during bear markets.*

Originally published at http://www.cxoadvisory.com/1801/size-effect/momentum-returns-for-large-caps/ on July 30, 2008.

Exploiting Industry Momentum Via ETFs?

June 27, 2008

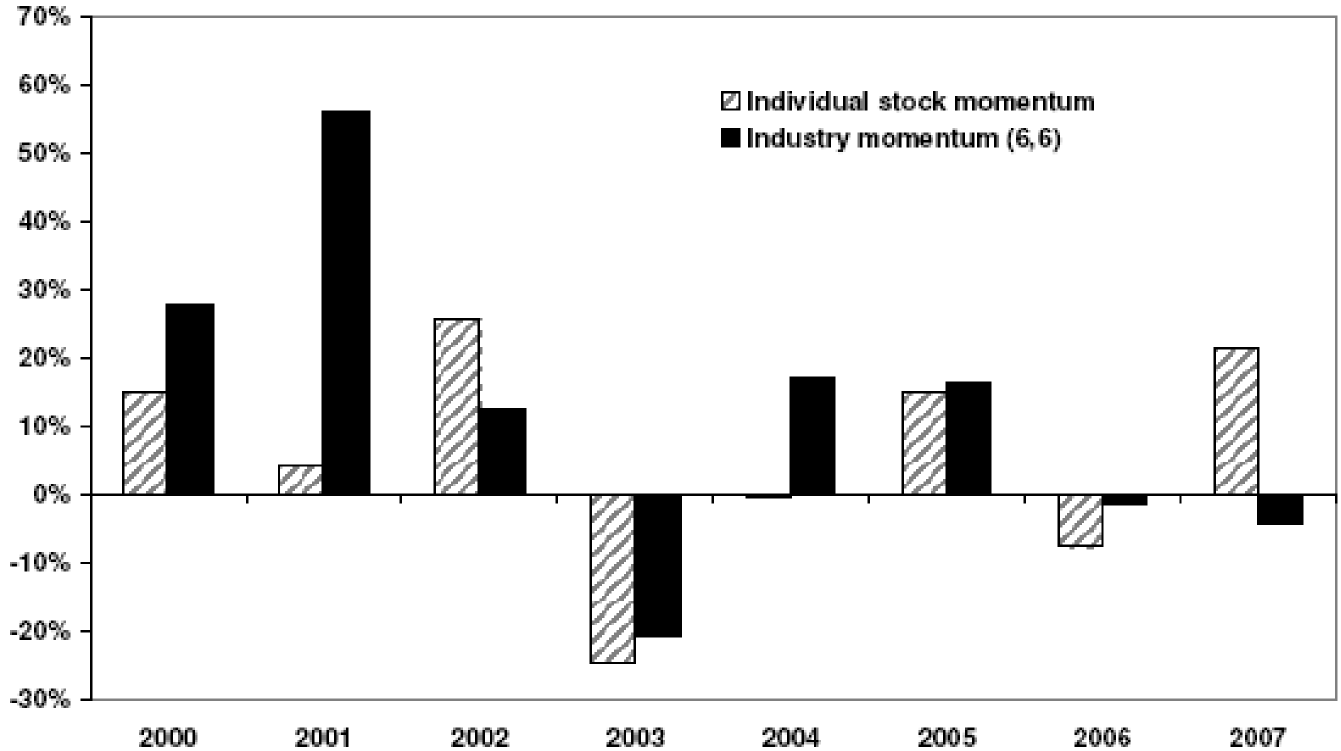
Industries arguably follow multi-month cycles of outperformance and underperformance. Can investors use industry/sector Exchange Traded Funds (ETF) to capture abnormal returns from industry momentum? In their June 2008 paper entitled "Can Exchange Traded Funds Be Used to Exploit Industry Momentum?", Laurens Swinkels and Liam Tjong-A-Tjoe analyze the profitability of industry momentum strategies based on two sets of industry/sector ETFs. Using monthly ETF return data for the period July 2000 through November 2007, *they conclude that:*

- Over the long run (1926-2007), medium-term industry momentum strategies that are self-financing (long-short) generate abnormal returns of about 0.4%-0.5% per month before trading frictions.
- Momentum effects have not disappeared since 2000 (see the chart below), with industry momentum generating abnormal returns (before trading frictions) of about 5% per year during 2000 to 2007.
- iShares Sector/Industry ETFs and Select Sector SPDRs track industry indexes reasonably well.
- A rolling momentum strategy that invests one sixth of the portfolio each month long (short) the sector ETF with the highest (lowest) past six-month return and holds each position for six months generates an abnormal return of 0.37% via iShares sector ETFs and 0.59% via Select Sector SPDRs, before trading frictions, over the period July 2000 through November 2007.
- Estimated bid-ask spreads, broker commissions and short-selling costs make these abnormal returns disappear for nearly all combinations of ranking and holding periods ranging from three months to 12 months.

The following chart, taken from the paper, shows the annual momentum returns during 2000-2007 for:

- Individual stocks from the data library of Kenneth French.
- The 10 industries defined in the data library of Kenneth French based on six-month ranking and six-month holding (6,6) periods.

The chart indicates that momentum effects have not disappeared in recent years.



In summary, *after accounting for trading frictions, medium-term long-short industry momentum strategies implemented via sector/industry ETFs do not offer abnormal returns.*

Note that the sample period of a little over seven years is quite short for this kind of analysis.

Originally published at http://www.cxoadvisory.com/1763/momentum-investing/exploiting-industry-momentum-via-etfs/ on June 27, 2008.

Returns of High-Momentum Stocks Around Earnings Announcements

May 7, 2008

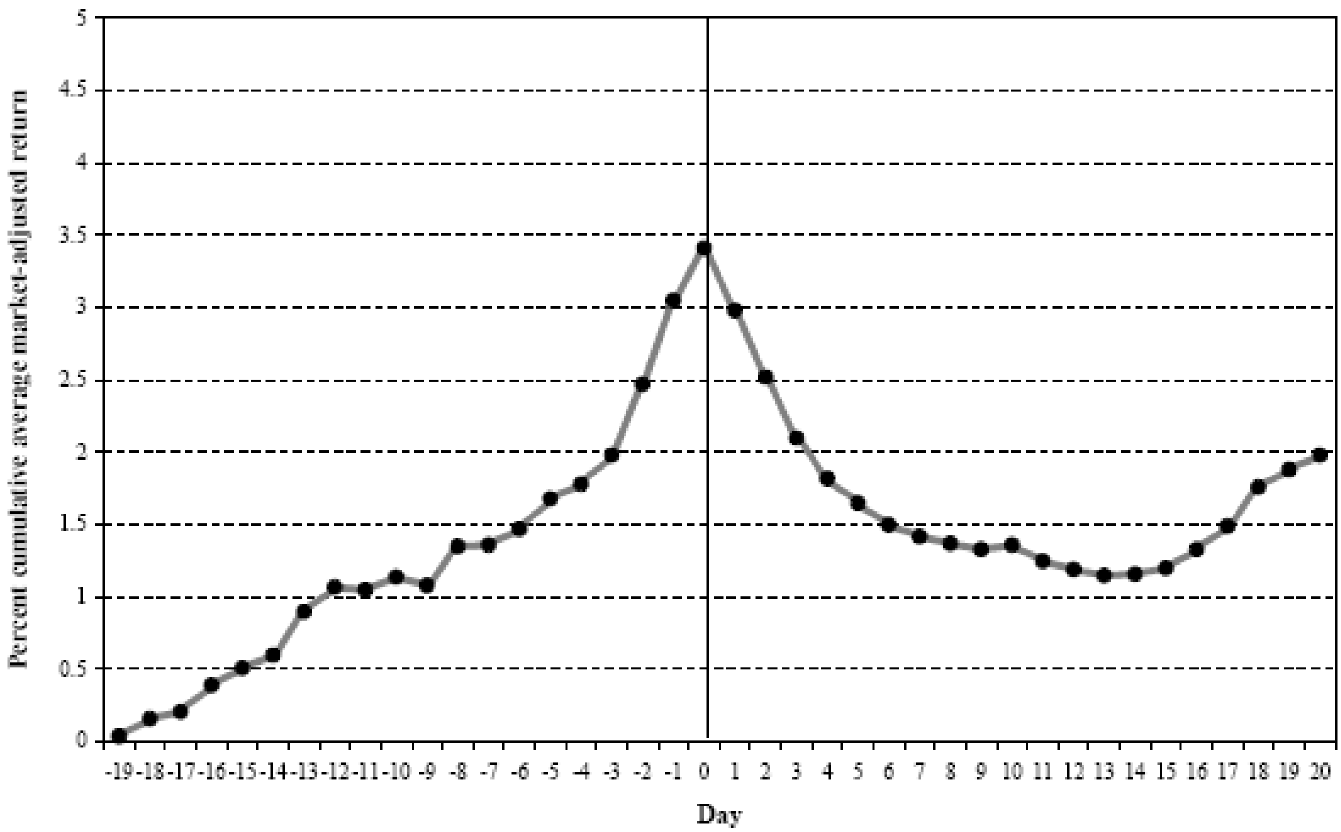
Do the attention-grabbing past returns of high-flying stocks produce pre-earnings announcement buying frenzies? In the April 2008 version of their paper entitled "Limited Attention and the Earnings Announcement Returns of Past Stock Market Winners", David Aboody, Reuven Lehavy and Brett Trueman examine whether the limited time and resources of small investors explains a striking return pattern around the earnings releases of firms with extremely strong prior year price momentum. Using daily stock return data and earnings release/forecast news from the beginning of 1971 through the third quarter of 2005 for a broad sample of companies, *they conclude that:*

- Stocks in the top 1% of prior year returns generate an average market-adjusted return of +1.58% (-1.86%) during the five trading days before (after) earnings announcements, excluding trading frictions.
- Within this set of high-fliers, stocks with earnings announcements unambiguously occurring outside of normal trading hours generate an average market-adjusted return of +3.09% (-3.05%) during the five trading days before (after) earnings announcements, including a significant close-to-open average return of +0.93% immediately after announcements as part of the pre-announcement return. In other words, going long these stocks five days before earnings announcements, closing the long positions at the first open after announcements and then shorting until the close five days later generates an average market-adjusted ten-day return of over 6%, excluding trading frictions.
- Assuming that all buys are at the ask and sells are at the bid to account for bid-ask spread reduces the above average abnormal returns to +0.94% (-0.85%) before (after) earnings announcements for all stocks in the top 1% of positive momentum and +1.66% (-1.34%) for the subset of these stocks with announcements clearly occurring outside of normal trading hours.
- Fore comparison, the average five-day pre-announcement (post-announcement) market-adjusted return for the entire sample of stocks is just +0.30% (-0.1%).
- Neither contemporaneous pre-release/post-release analyst earnings forecast revisions nor negative earnings surprises explain the anomalous returns.
- There is evidence of a pre-announcement order imbalance for small and medium-sized traders that disappears post-announcement, suggesting that trading decisions of individual investors drive the anomaly.

The following chart, taken from the paper, shows the cumulative average market-adjusted return for stocks in the top 1% of prior year raw returns from 19 days before earnings announcements (-19) to 20 days after earnings announcements (+20) over the entire sample period. Day 0 is the earnings announcement day. The mean daily market-adjusted return is:

- +0.11% from days -19 through -5;
- +0.35% from days -4 through 0
- -0.35% for days 1 through 5;
- -0.06% for days 6 through 13; and,
- +0.12% for days 14 through 20.

The 1.98% cumulative average market-adjusted return over the entire 40-day period represents a momentum return of about 1% per month.



In summary, *traders may be able to exploit an attention-driven anomaly for very high momentum stocks by going long from five days before to the morning after earnings announcement and short the next five days.*

Originally published at http://www.cxoadvisory.com/1724/animal-spirits/returns-of-high-momentum-stocks-around-earnings-announcements/ on May 7, 2008.

Classic Paper: Physical Inventories and Commodity Futures Returns

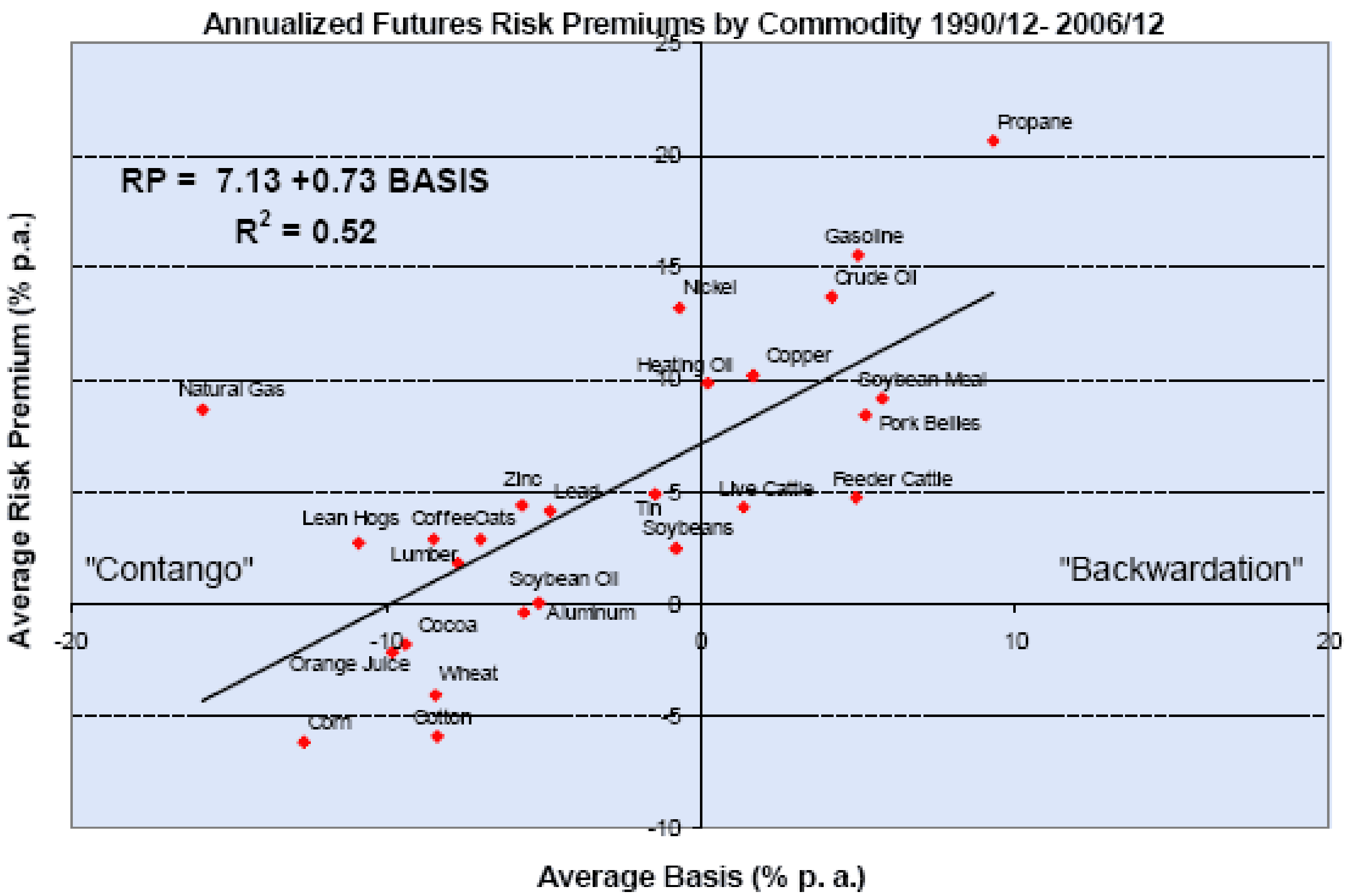
April 28, 2008

We occasionally select for retrospective review an all-time "best selling" research paper from the past few years from the General Financial Markets category of the Social Science Research Network (SSRN). Here we summarize the June 2007 paper entitled "The Fundamentals of Commodity Futures Returns" (download count over 2,500) by Gary Gorton, Fumio Hayashi and Geert Rouwenhorst. Commodity futures are derivative, short-maturity claims on real assets. In this paper, the authors apply the theory of storage to investigate relationships between the physical inventories of these assets and the returns to traders in the associated commodity futures. Using monthly data for over 30 commodity futures and associated physical inventories as available between 1969 and 2006 and data from the weekly Commodity Futures Trading Commission Commitments of Traders (COT) reports, *they conclude that:*

- Of the 33 commodity futures examined, 26 (21) earn positive arithmetic (geometric) average excess returns. An equally weighted index of these futures earns an average annual excess return of 5.48%.
- The correlations among returns for commodity futures are positive but generally small.
- Commodity futures prices mostly exceed contemporaneous spot prices (are in contango).
- Spot returns, futures basis (percentage difference between the current spot price and current nearest-to-maturity futures price, also called "roll yield" or "roll return") and past futures returns reflect inventory levels and are informative about commodity futures risk premiums. Specifically, low inventories indicate high commodity futures risk premiums.
- Low commodity inventory levels are associated with futures prices in backwardation (positive roll return), while high inventories are associated with futures prices in contango (negative roll return).
- Over the entire sample period, a portfolio of commodities in backwardation (contango) outperforms (underperforms) an equally weighted index by an average 5.4% (4.8%) per year. A hedge portfolio that is long (short) commodity futures with high (low) basis generates positive returns in 58% of sample months with an average annual return of 10.2%. (See the chart below.)
- A hedge portfolio that is long (short) commodity futures with high (low) momentum also generates positive returns in 58% of sample months with an average annual return of 13.4%. Momentum returns may derive from the slow recovery of commodity inventories from shocks.
- Backwardation and momentum strategy returns stem from selecting commodities subject to high price volatility due to low inventories and thereby earning a premium for bearing volatility risk.
- Aggregate positions of commodity futures traders correlate with both contemporaneous

inventories and contemporaneous futures prices. Commercial traders increase short positions after prices spike and when inventories are high. Non-commercial traders increase long positions in commodities with high momentum and, to a lesser extent, positive roll return. However, there is no evidence that net positions (hedging pressure) independently correlate with futures risk premiums.

The following chart, taken from the paper, plots average annualized futures risk premium versus average annualized futures basis (roll return) for individual commodity futures from December 1990 through December 2006. The basis compares futures prices to contemporaneous spot prices, while the risk premium is the difference between futures prices and expected future spot prices. A positive (negative) basis indicates commodity futures in backwardation (contango). A simple linear regression has an R-squared statistic of 0.52, indicating that variation in basis explains 52% of the risk premium. In general, futures prices must exceed contemporaneous spot prices to compensate inventory holders for the cost of storage. Only when inventories are unusually low can the spot price exceed the futures price corrected for storage cost.



In summary, *physical inventory levels are the critical determinants of commodity future price variations and returns, intermediating both backwardation (positive roll) returns and momentum returns. After accounting for inventory effects, there is no evidence that the aggregate position of traders (hedging pressure) predicts commodity futures risk premiums.*

Originally published at http://www.cxoadvisory.com/1707/momentum-investing/classic-paper-physical-inventories-and-commodity-futures-returns/ on April 28, 2008.

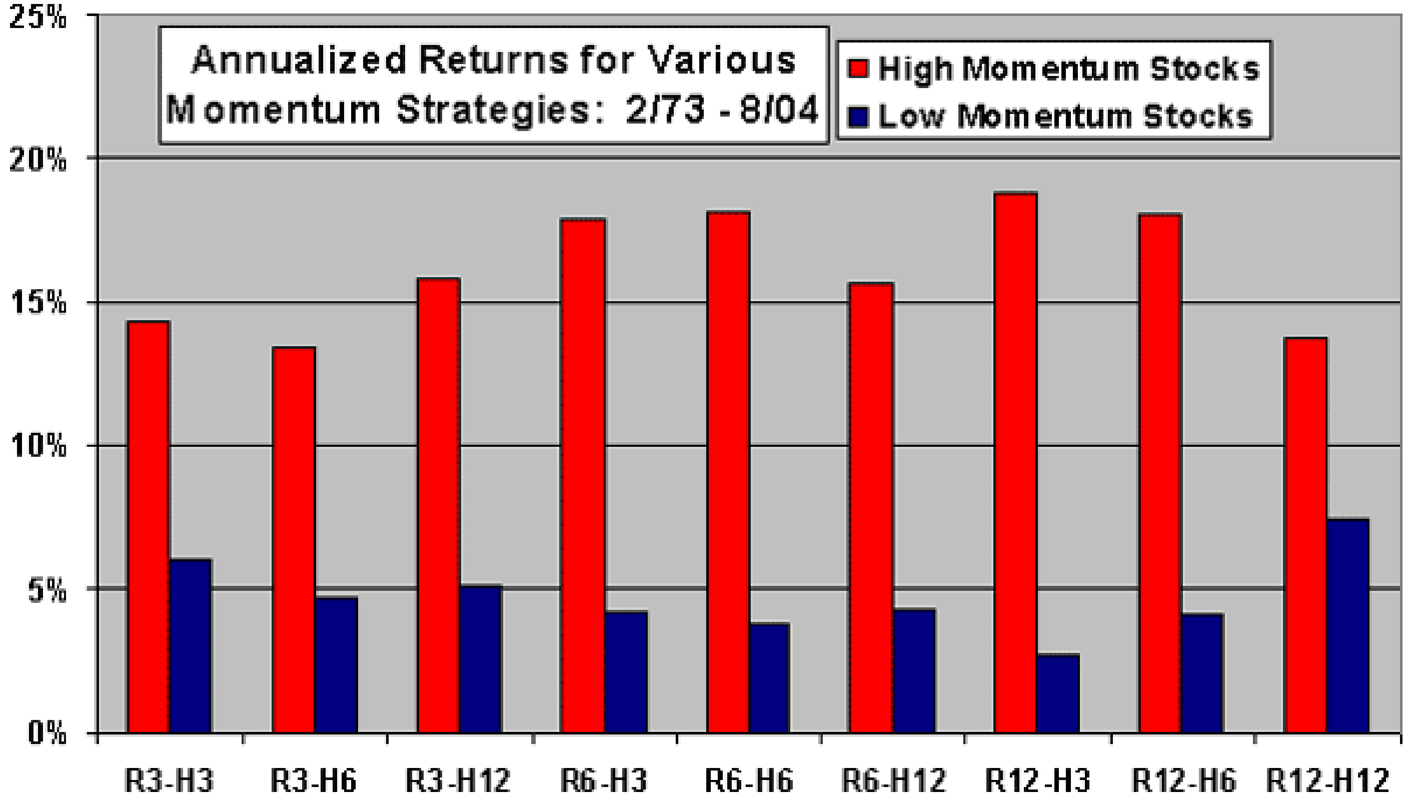
Momentum and Contrarian Commodity Futures Returns

April 10, 2008

Do commodity futures exhibit short-term momentum and long-term reversion, as do stocks? In the August 2006 version of their paper entitled "Momentum Strategies in Commodity Futures Markets", Joelle Miffre and Georgios Rallis examine the profitability of 32 momentum (short-term continuation) and 24 contrarian (long-term reversal) strategies in commodity futures markets. The momentum strategies buy (sell) recently outperforming (underperforming) commodity futures and hold resulting long-short portfolios up to 12 months. The contrarian strategies buy (sell) the commodity futures that underperformed (outperformed) in the distant past and hold resulting long-short portfolios for periods of two to five years. All strategies trade liquid futures contracts with nearby maturities involving 31 commodities, unimpeded by short-selling restrictions often encountered in equity markets. Using futures contract price data spanning 1/31/79-9/30/04, *they conclude that:*

- Contrarian (long-term reversal) strategies do not work for commodity futures. There is no evidence that past winners (losers) turn into losers (winners) over ranking and holding periods of two to five years. In fact, past losers tend to keep losing.
- There are 13 profitable long-short momentum strategies for commodity futures with an average annual return over the entire sample period of 9.38%, compared to loss of 2.64% for a long-only equally-weighted futures portfolio. Shorting past losers drives profitability. While these results exclude transaction costs, such costs are very low for commodity futures contracts.
- The most profitable momentum strategy (12-month ranking period, one-month holding period) offers an average annual return of 14.6%, but it is also the second most volatile strategy with a annualized standard deviation of 25.6%.
- Commodity futures momentum returns do not diminish over the sample period.
- Successful momentum strategies tend to buy contracts in backwardation and sell contracts in contango.
- The correlation between commodity futures momentum returns and the returns of stocks and bonds is low, making commodity futures momentum portfolios good risk diversifiers.
- The correlation between commodity futures momentum returns and the change in the consumer price index is insignificant, indicating that they do not hedge against short-term inflation.

The following chart, taken from the paper, summarizes the average returns for 32 commodity futures long-short momentum strategies based on combinations of four ranking periods and eight holding periods during 1/31/79-9/30/04. It shows that momentum returns are mostly short-term and that, for commodities, there is no significant long-term reversal of momentum.



In summary, *commodity futures long-short momentum strategies may offer both good average returns and effective diversification of a stocks/bonds portfolio.*

Originally published at http://www.cxoadvisory.com/1684/momentum-investing/momentum-and-contrarian-commodity-futures-returns/ on April 10, 2008.

Institutional Trading, Returns and Strength of Anomalies

April 1, 2008

Are there exploitable differences in returns for stocks with heavy versus light institutional trading activity? In his March 2008 paper entitled "Trader Composition and the Cross-Section of Stock Returns", Tao Shu analyzes the impact of institutional trading activity on the returns of individual stocks and on the strength of the momentum effect, post earnings-announcement drift (PEAD), the value premium and the investment effect. He calculates institutional trading activity at a quarterly frequency by dividing the aggregate absolute change in reported institutional holdings of a stock by the contemporaneous total quarterly trading volume for the stock. Using holdings data as reported via SEC Form 13F and associated stock trading volume and return data for the period 1980-2005, *he concludes that:*

- Institutions account for about half of all trading volume.
- Institutional trading activity is significantly different from institutional ownership, with a correlation of only 0.41.
- Both institutional ownership and firm characteristics affect institutional trading activity, but the most important determinant is historical trading activity. Persistence in institutional trading activity is stronger for stocks with light analyst coverage.
- Stocks with low institutional trading activity underperform stocks with high institutional trading activity by 0.25% to 0.53% per month depending on risk adjustments applied. The difference in performance is most pronounced for liquid stocks (1.03% per month for the most liquid but practically zero for the least liquid).
- Major return anomalies are much stronger in stocks with low institutional trading activity. Controlling for institutional ownership and other factors, stocks in the lowest third of institutional trading in the prior quarter compared to those in the top third (re-ranked monthly) exhibit:
    - Momentum (six-month formation period, one-month skip period and six-month holding period) stronger by 0.40% per month.
    - PEAD (from two days before announcement through one day after) stronger by 0.46% per month.
    - A value (high book-to-market minus low) premium larger by 0.97% per month.
    - An investment effect (low capital investment minus high) bigger by 0.57% per month.
- These findings suggest a positive relationship between (presumably informed and sophisticated) institutional trading activity and market efficiency.

In summary, *evidence suggests that stocks with low institutional trading activity (distinct from institutional ownership) tend to be overpriced, with amplified return anomalies.*

Originally published at http://www.cxoadvisory.com/1668/value-premium/institutional-trading-returns-and-strength-of-anomalies/ on April 1, 2008.

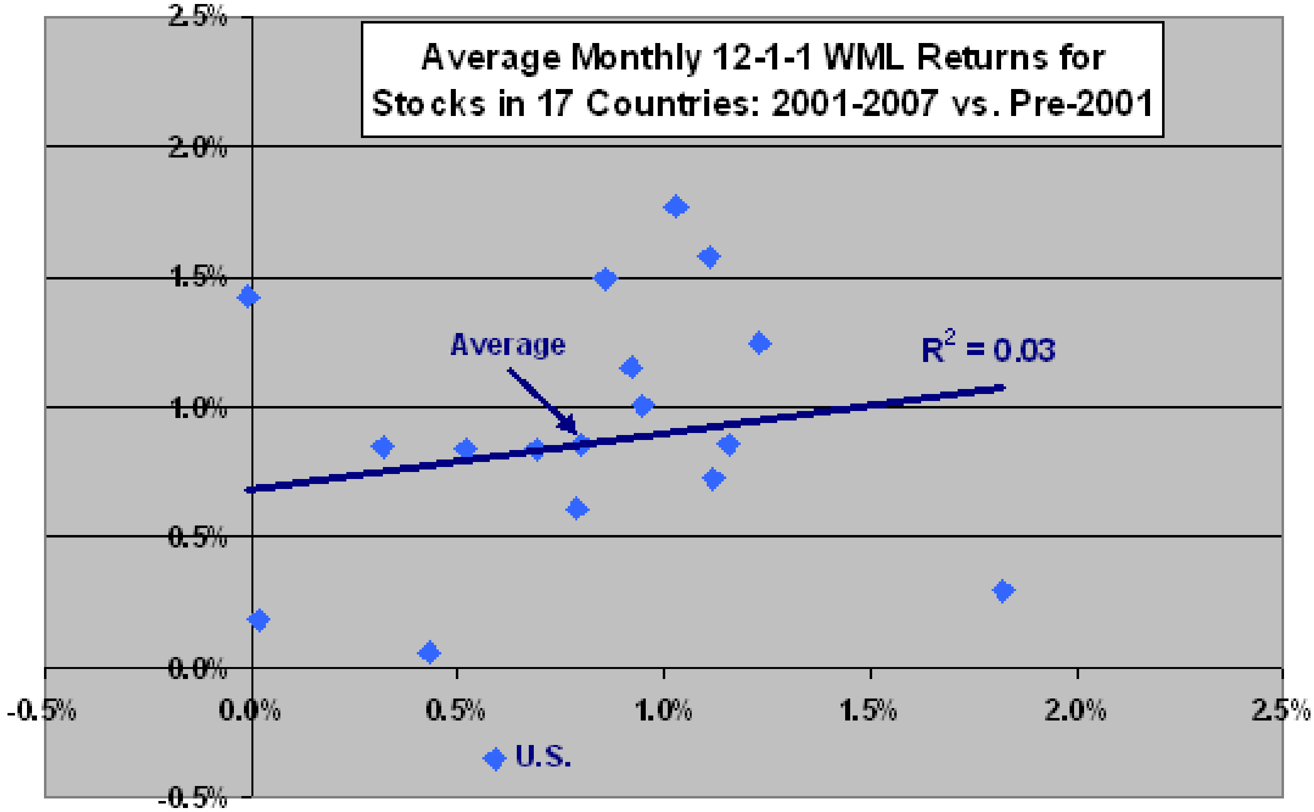
The Pervasiveness and Persistence of Momentum

February 20, 2008

Is the momentum effect pervasive across different equity markets and persistent through different time periods? The overview of Chapter 3 in "Global Investment Returns Yearbook 2008: Synopsis", which summarizes annual work performed by by Elroy Dimson, Paul Marsh and Mike Staunton for ABN AMRO, provides "findings from the longest momentum study ever undertaken." Applying a 12-1-1 strategy (rank returns over the past 12 months, wait one month and then hold for one month until rebalancing) to very long-run UK data and more recent data for each of 17 country stock markets, *they conclude that:*

- For a 12-1-1 momentum strategy applied to UK stocks during 1956-2007 (excluding trading frictions):
  - Stocks in the top fifth of past returns outperform those in the bottom fifth by a mean 10.8% (12.0%) per year on a value-weighted (equal-weighted) basis.
  - Selecting winners/losers using a more restrictive top/bottom tenth increases the winner-minus-loser (WML) return gap.
  - Limiting the universe of stocks to the Top 100 reduces the WML return gap to 7.0% year, but the relatively high liquidities of these stocks facilitate momentum strategy implementation.
- For a 12-1-1 momentum strategy applied to the Top 100 UK stocks during 1900-2007 (again, excluding trading frictions), those in the top fifth of past returns outperform those in the bottom fifth by a mean 10.3% per year on a value-weighted basis.
- These momentum returns are generally robust to the choice of ranking period, holding period, value versus equal weighting, definition of winners and choice of sample. However:
  - There are periods when winners underperform losers, sometimes substantially.
  - For the 12-1-1 strategy, monthly winner and loser turnovers average 31% and 33%, respectively, and the resulting trading costs may seriously impact performance.
- The average monthly 12-1-1 WML return across 17 countries is 0.86% for 2001-07, compared to 0.80% up to the end of 2000 (from another study). The U.S. is the only market for which WML returns are negative during 2001-2007.

The following chart, constructed from data in the synopsis, relates average monthly 12-1-1 WML returns for stocks in 17 countries during 2001-2007 to the WML returns for the same countries up to the end of 2000. The Pearson correlation between the two series is 0.17, and the R-squared statistic is 0.03. These results offer little evidence that investors can use past momentum returns to anticipate future momentum returns on a country-by-country basis. Note that U.S. stocks have the lowest (and negative) momentum returns for 2001-2007.



In summary, *in the words of the authors: "The momentum effect, both in the UK and globally, has been pervasive and persistent. Though costly to implement on a standalone basis, all investors need to be acutely aware of momentum. Even if they do not set out to exploit it, momentum is likely to be an important determinant of their investment performance."*

Originally published at http://www.cxoadvisory.com/1617/momentum-investing/the-pervasiveness-and-persistence-of-momentum/ on February 20, 2008.

Fama and French Dissect Anomalies

January 14, 2008

Which stock return anomalies are trustworthy, and which are not? In the June 2007 draft of their paper entitled "Dissecting Anomalies", Eugene Fama and Kenneth French apply both sorts and regressions to examine the robustness of the momentum, net stock issuance, accruals, profitability and asset growth anomalies. They note that sorts on an anomaly variable offer a simple picture of how average returns vary, but microcaps (a few big stocks) can dominate the performance of a sort-based equal-weighted (value-weighted) hedge portfolio. In addition, sorts are ill-suited to determinations of: (1) the exact relationship between an anomaly variable and returns, and (2) relationships among anomalies. They note also that extreme behavior by microcaps and outliers generally can distort inference from regressions. Using a robust set of firm data for a broad set of U.S. stocks allocated to three size groups (microcap, small and big) over the period 1963-2005, *they conclude that:*

- On average, microcaps are roughly 60% of sampled stocks, but they represent only about 3% of total market value (compared to 90% for big stocks). They boast a high average equal-weighted (EW) monthly return of 1.56% (1.07% for big stocks), but they also have the highest return volatility by far.
- Using sorts based on anomaly variables, adjusted for size and book-to-market (B/M) factors:
    - Momentum, net stock issuance and accruals relate to large abnormal returns for all size groups. The EW and value-weighted (VW) abnormal hedge portfolio returns for these three variables are strong across all size groups.
    - Abnormal returns after net stock issues and accruals derive mostly from extreme values of these variables.
    - Higher positive profitability relates to higher abnormal returns, but negative profitability does not lead to abnormally low returns.
    - There is no asset growth anomaly for big stocks.
- Using regressions of stock returns on anomaly variables:
    - Size owes much of its predictive power to microcaps. Its effect is marginal for small and big stocks.
    - The relationship between average returns and B/M is moderate and consistent across size groups.
    - Momentum and net stock issuance exhibit the strongest average regressions across all size groups. Momentum effects are only about half as strong for microcaps as for small and big stocks.
    - Positive accruals relate negatively to average returns for all size groups.
    - Among profitable firms, profitability relates positively to average returns for all size groups.
    - The negative relationship between asset growth and average returns is powerful for microcaps, weaker but statistically reliable for small stocks and largely non-

existent for big stocks.

- All these anomaly variables are at least rough proxies for expected cash flows and therefore reasonably affect valuations.

The following chart organizes key findings from the paper.

Anomaly Tested	Via Sorts Adjusted for Size and B/M	Via Regressions
Size		Concentrated in microcaps; marginal for small and big stocks.
Book-to-Market (B/M)		Generally consistent across size groups, but somewhat smaller for big stocks.
Momentum	Strong for all size groups, and very systematic from low to high momentum. Strong positive equal-weighted (EW) and value-weighted (VW) hedge returns.	Strong average regression slopes for all size groups; only about half as strong for microcaps.
Net stock issuance	Strong for all size groups, but driven by extremes of net issuance. Large negative EW and VW hedge returns. Pervasive positive abnormal returns after repurchases, but no consistently negative returns after sales. Most extreme abnormal returns after largest repurchases. However, positive abnormal returns after moderately positive stock issues.	Strong, indistinguishable average regression slopes for all size groups.
Accruals	Strong for all size groups, but limited to the extremes of accruals. Large negative EW and VW hedge returns. Positive abnormal returns for negative accruals, but strong negative abnormal returns only for the most positive accruals. Positive abnormal EW returns that do not decline much across sorts for less extreme accruals (positive and negative). Except for microcaps, only small EW abnormal returns for less extreme accruals.	Pervasive negative relation between accruals and average returns for positive accruals; regressions are not consistently strong.
Asset growth	Systematic negative relationship between asset growth and abnormal returns only for microcaps. Large average EW and VW hedge portfolio returns for microcaps and small stocks. No abnormal returns on big stocks that represent more than 90% of market.	Powerful among microcaps; weaker but statistically reliable among small stocks; probably non-existent among big stocks.
Profitability	Higher positive profitability tends to be associated with higher abnormal returns; no evidence that negative profitability relates to abnormally low returns. Only the small group yields notable EW and VW hedge returns and average returns that increase systematically from unprofitable to extremely profitable firms.	Reliable evidence of an overall positive relationship between positive profitability and average returns. May be stronger for profitable small stocks than for profitable microcaps and big stocks.

	increase systematically from unprofitable to extremely profitable firms.	microcaps and big stocks.

In summary, *some anomalies are stronger and more consistent than others. Momentum appears to be the strongest and most consistent.*

Originally published at http://www.cxoadvisory.com/1582/big-ideas/fama-and-french-dissect-anomalies/ on January 14, 2008.

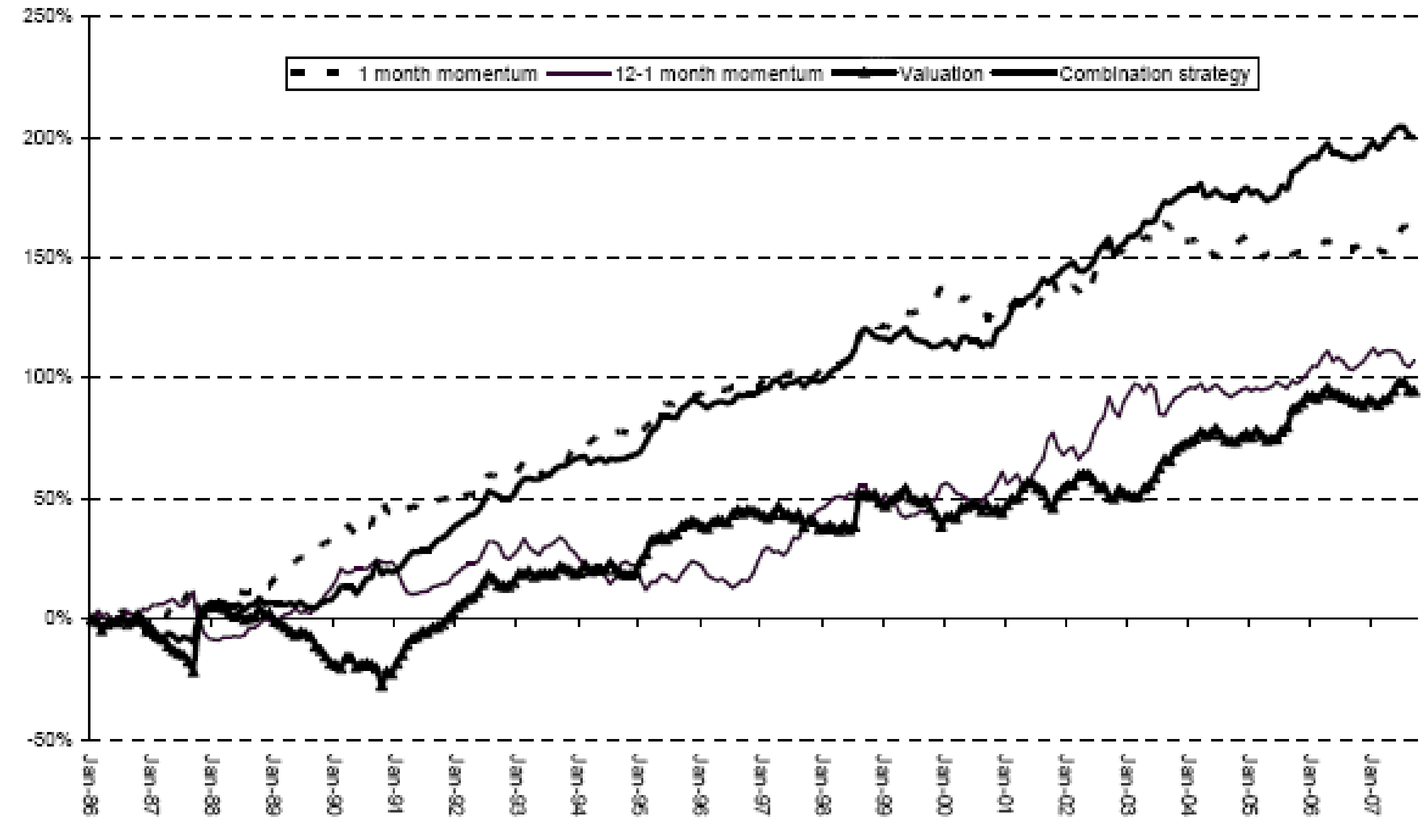
Combined Value-Momentum Tactical Asset Class Allocation

January 7, 2008

Are value and momentum anomalies reliably present across international asset classes? If so, can investors exploit them to generate abnormal returns? In the December 2007 version of their paper entitled "Global Tactical Cross-Asset Allocation: Applying Value and Momentum Across Asset Classes", David Blitz and Pim van Vliet examine global tactical asset allocation strategies across a broad range of asset classes based on both value (asset yield or earnings yield) and momentum (both short-term and long-term). These strategies weight asset classes according to volatility, with higher (lower) weights assigned to classes with lower (higher) volatilities. Using price and yield data for 12 international asset classes spanning January 1985 through September 2007, *they conclude that:*

- Hedge, or zero-investment, portfolios that are long (short) the top (bottom) quarter of asset classes, rebalanced monthly over the entire sample period, generate average annual returns before transaction costs of:
  - 4.4% based on valuation;
  - 5.0% based on 12-1 momentum (calculated from the past 12 months excluding the most recent month); and,
  - 7.4% based on 1-month momentum.
- Correlations among the returns of these strategies are fairly weak (and negative between valuation and the two types of momentum), suggesting distinct effects.
- A hedge portfolio that is long (short) the top (bottom) quarter of asset classes based on a combination of valuation and momentum generates an annualized return of over 9% before transaction costs (perhaps 7% after transaction costs) over the entire sample period.
- Outperformance of this strategy is stable over time and present in a 1974-1985 out-of-sample test on a reduced set of asset classes.
- The return cannot be explained as a reward-for-risk proposition using commonly used risk factors (market, size, value and momentum).
- Financial markets at the asset class level may be inefficient because there is not enough "smart money" to eliminate mispricings.

The following chart, taken from the paper, presents the cumulative performance of the individual and combination hedge portfolios described above. It shows that the performance of the portfolios is generally stable across the entire sample period.



In summary, *value and momentum investing may work across a broad range of asset classes, and the two effects are independent enough that combining them may yield incremental outperformance.*

A reader asked: “I’m really interested in applying this strategy, but after reading through it several times I still don’t understand how to apply it. Can you restate the strategy in simpler terms?”

> The strategy, summarized in “Combined Value-Momentum Tactical Asset Class Allocation”, defines attractive and unattractive asset classes by ranking 12 classes based on a combination of momentum and value measurements. Specifically, quoting from the paper:
>
>> “At the end of every month we rank all assets based on their momentum and/or valuation scores, and use this ranking to assign the assets to four quartile portfolios consisting of three assets each. We then calculate the return of each quartile portfolio over the following month.” The use of quartiles is somewhat arbitrary, trading purity of attractiveness/unattractiveness for diversification.
>
> To rank assets for the momentum-only strategies tested in the paper:
>
>> “We will examine both a 1-month return strategy and a classic 12-1 month (12 months excluding the most recent month) momentum strategy.”

To rank assets for the valuation-only strategy tested in the paper:

> "The starting point of our approach is to take a simple yield measure for each asset class. …we apply a limited number of asset-specific, fixed adjustments to the basic yield data. These adjustments were chosen in such a way that the main structural biases towards certain asset classes are removed. …these adjustments result in scores that are much more comparable across asset classes. In fact, after applying the adjustments, the long-term average valuation score for every asset falls in a range between -1% and +1%, which implies that structural biases towards certain asset classes are effectively eliminated."

To rank assets for the combined momentum-valuation strategy tested in the paper (the one that interests you):

> "A combined score for each asset class is calculated by taking a weighted average of its rank (1 to 12) on the individual variables. We choose a simple 50/50 balance between the momentum and valuation strategies and equal weighting of the two momentum variables. This translates into weights of 25% for 1-month momentum, 25% for 12-1 month momentum and 50% for valuation."
>
> For example, if a certain asset class ranks 4th for 1-month momentum, 8th for 12-1 momentum and 6th for valuation, its combined rank would be: 0.25*4 + 0.25*8 + 0.5*6 = 6. A portfolio that is long the assets with the top three combined ranks and short the assets with the bottom three combined ranks, reformed monthly, generates the 11.9% annual return (before trading frictions) stated in the paper. The use of 25%/25%/50% weights is arbitrary.

The yield adjustments that allow ranking different asset classes by valuation vary by asset class. Specifically:

- "for the government bond assets, US Treasuries and German and Japanese government bonds, we subtract 1% from the term premiums, which adjusts for the fact that the yield curve tends to be upward sloping;
- "for US investment grade credits we subtract 2% and for US high yield bonds 6%, also to adjust for the slope of the yield curve, and additionally to adjust for default risk;
- "for emerging markets equities we subtract 1% to adjust for the structurally lower P/E compared to mature equity markets;
- "for US real estate equities we subtract 2% to adjust for the structurally higher yield compared to regular equities."

You would have to construct and maintain an adjusted yield dataset for each asset class of interest. If you introduce asset classes beyond those used by the authors, you would have to determine appropriate yield adjustments for them. You could probably do the yield adjustments empirically (instead of top-down, as the authors do) by picking a base asset class (e.g., U.S. equities) and regressing yields from other classes against the yield of the base class to derive adjustments. The yield adjustments are perhaps the hardest part of the approach.

Originally published at http://www.cxoadvisory.com/1574/value-premium/combined-value-momentum-tactical-asset-class-allocation/ on January 7, 2008.

Trading Friction as a Momentum Killer

August 16, 2007

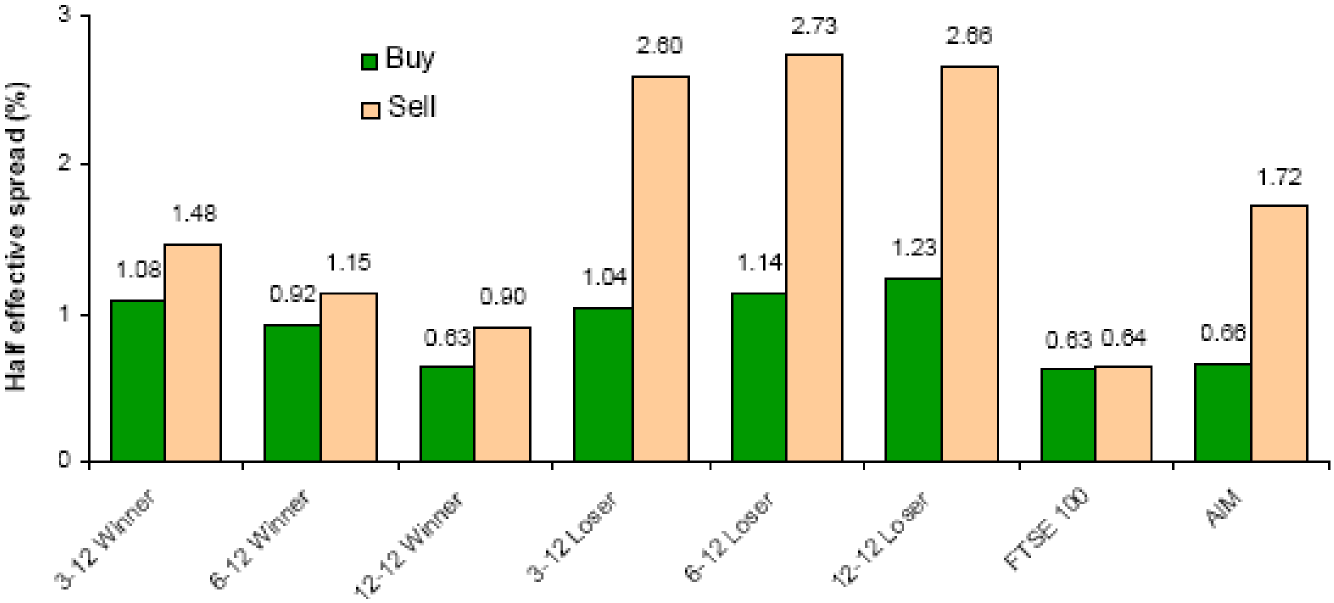
Are momentum trading strategies profitable after accounting for trading costs? In their August 2007 draft paper entitled "Low-Cost Momentum Strategies", Xiafei Li, Chris Brooks and Joelle Miffre analyze the impact of transaction costs on the profitability of momentum strategies for UK stocks. They consider all combinations of 3-month, 6-month and 12 month ranking and holding periods. Using stock price data for 3,520 UK companies and separately for the constituents of the FTSE 100 index (large capitalization stock sample) and the Alternative Investment Market (AIM – small capitalization stock sample) over the period 1986-2005, *they conclude that:*

- Across all strategies, before trading costs, the portfolios that are long past winners and short past losers earn an average monthly return of 1.9%, ranging from 1.6% for the 3-3 strategy to 2.2% for the 12-3 strategy. Momentum profits come mostly from the short positions, with past losers (winners) producing an average monthly return of -1.6% (0.32%). Momentum stocks, especially past losers, tend to have relatively low price, market capitalization and trading volume.
- Average total round-trip trading friction based on quoted spread is 6.7% (3.8%) for past losers (winners). These costs effectively offset the above momentum portfolio returns.
- Past losers are more expensive to trade than past winners due to the high cost of shorting stocks them (selling costs average 2.3 times higher for past losers than for past winners).
- A low-cost momentum strategy that focuses on the past winners and past losers with relatively low total transaction costs does generate abnormal returns. Momentum portfolios that are long past winners and short past losers with the 10%, 20% and 50% lowest total transaction costs generate average net annual returns of 19.1%, 15.5% and 12.6%, respectively. Among all such strategies, the 12-12-10% (12-month ranking period, 12-month holding period, among 10% of stocks with lowest transaction costs) is the most profitable with an average 27.7% net annual return.

The following chart, taken from the paper, shows the average estimated effective half-spreads for buyer-initiated (Buy) and seller-initiated (Sell) trades for three past winner portfolios, three past loser portfolios, and for the average stock in the FTSE 100 and AIM indexes. Overall, the chart shows that shorting of small capitalization past losers is costly. Specifically:

- Selling small capitalization stocks (AIM) is more costly than selling large capitalization stocks (FTSE 100), and more costly than buying any size stock.
- Selling past winners is only a little more costly than buying past winners.
- Selling past losers is much more costly than buying past losers.

Momentum strategies that ignore transaction costs tend not to outperform because of the high transaction costs of selling past losers.



In summary, *successful momentum trading may depend critically on restricting consideration to stocks with the lowest total transaction costs.*

Originally published at http://www.cxoadvisory.com/1388/momentum-investing/trading-friction-as-a-momentum-killer/ on August 16, 2007.

The 52-Week High as a Momentum Indicator for Individual Stocks

May 23, 2007

A reader notes and asks: “It is frequently said that stocks at 52-week highs are the most likely to outperform in the future. Is there any academic evidence to support this assertion?” In their October 2004 *Journal of Finance* article entitled “The 52-Week High and Momentum Investing”, Thomas George and Chuan-Yang Hwang examine the explanatory power of the 52-week high in the context of momentum investing. They compare the 52-week high as a momentum indicator to benchmark momentum strategies that employ six months of past returns to forecast six months of future returns. Using price data for a broad range of stocks over the period 1963-2001, *they find that:*

- Based on raw returns across the calendar year, nearness to the 52-week high is comparable to other momentum indicators in forecasting future returns. (See the first table below.) In fact, a large part of the profit from long/short momentum strategies based on past returns comes from stocks whose prices are close to/far from their 52-week highs.
- Proximity to the 52-week high has predictive power whether or not stocks exhibit past return-based momentum, suggesting that price level may be more important than past price change in explaining momentum.
- A 52-week high momentum strategy outperforms other momentum strategies for January-segregated returns. (See the second table below.)
- A 52-week high momentum strategy generates risk-adjusted (for market capitalization and liquidity) returns about twice as large as those associated with other momentum strategies. The outperformance is even larger outside of January.
- Future returns predicted by the 52-week high do not reverse in the long run.
- Results are robust to calculating momentum based on 12 months of past returns rather than six months, and to using 12 months of future returns rather than six months.

The following table, extracted from the paper, compares average monthly returns during July 1963 through December 2001 for winner and loser momentum portfolios held for six months after formation:

1. Jegadeesh-Titman (JT) winner (loser) portfolios are the equally weighted 30% of stocks with the highest (lowest) past six-month returns.
2. Moskowitz-Grinblatt (MG) winner (loser) portfolios are the equally weighted top (bottom) 30% of stocks ranked by the six-month value-weighted return for the industry to which the stock belongs.
3. 52-week high winner (loser) portfolios are the equally weighted 30% of stocks with the highest (lowest) ratio of current price to 52-week high.

The average monthly return for zero-cost portfolios that are long winners and short losers is about 0.45% for all three strategies. A large part of the JT strategy profit comes from stocks with prices close to and far from their 52-week highs.

	Winner	Loser
JT's individual stock momentum	1.53%	1.05%
MG's industrial momentum	1.48%	1.03%
52-week high	1.51%	1.06%

The next table, also extracted from the paper, emphasizes the criticality of a January effect to two of these three momentum strategies. It shows that momentum effects tend to reverse in January, such that long-short momentum portfolios generate larger returns for February through December but lose money in January. Said differently, loser stocks (but not loser industries) rebound in January. The table also shows that the January-segregated 52-week high strategy results are stronger than those of the other two momentum strategies.

	Winner	Loser
January Returns Excluded		
JT's individual stock momentum	1.23%	0.16%
MG's industrial momentum	0.99%	0.50%
52-week high	1.30%	0.07%
January Only		
JT's individual stock momentum	4.96%	11.2%
MG's industrial momentum	7.00%	7.09%
52-week high	3.84%	12.11%

The authors interpret these results as follows: “Traders appear to use the 52-week high as a reference point against which they evaluate the potential impact of news. When good news has pushed a stock’s price near or to a new 52-week high, traders are reluctant to bid the price of the stock higher even if the information warrants it. The information eventually prevails and the price moves up, resulting in a continuation. Similarly, when bad news pushes a stock’s price far from its 52-week high, traders are initially unwilling to sell the stock at prices that are as low as the information implies. The information eventually prevails and the price falls. In this respect, traders’ reluctance to revise their priors is price-level dependent. The greatest reluctance is at price levels nearest and farthest from the stock’s 52-week high. At prices that are neither near nor far from the 52-week high, priors adjust more quickly and there is no pronounced predictability when information arrives.”

In summary, *the 52-week high is on average a superior indicator of positive momentum for individual stocks (except for a January reversal).*

Originally published at http://www.cxoadvisory.com/1284/technical-trading/the-52-week-high-as-a-momentum-indicator-for-individual-stocks/ on May 23, 2007.

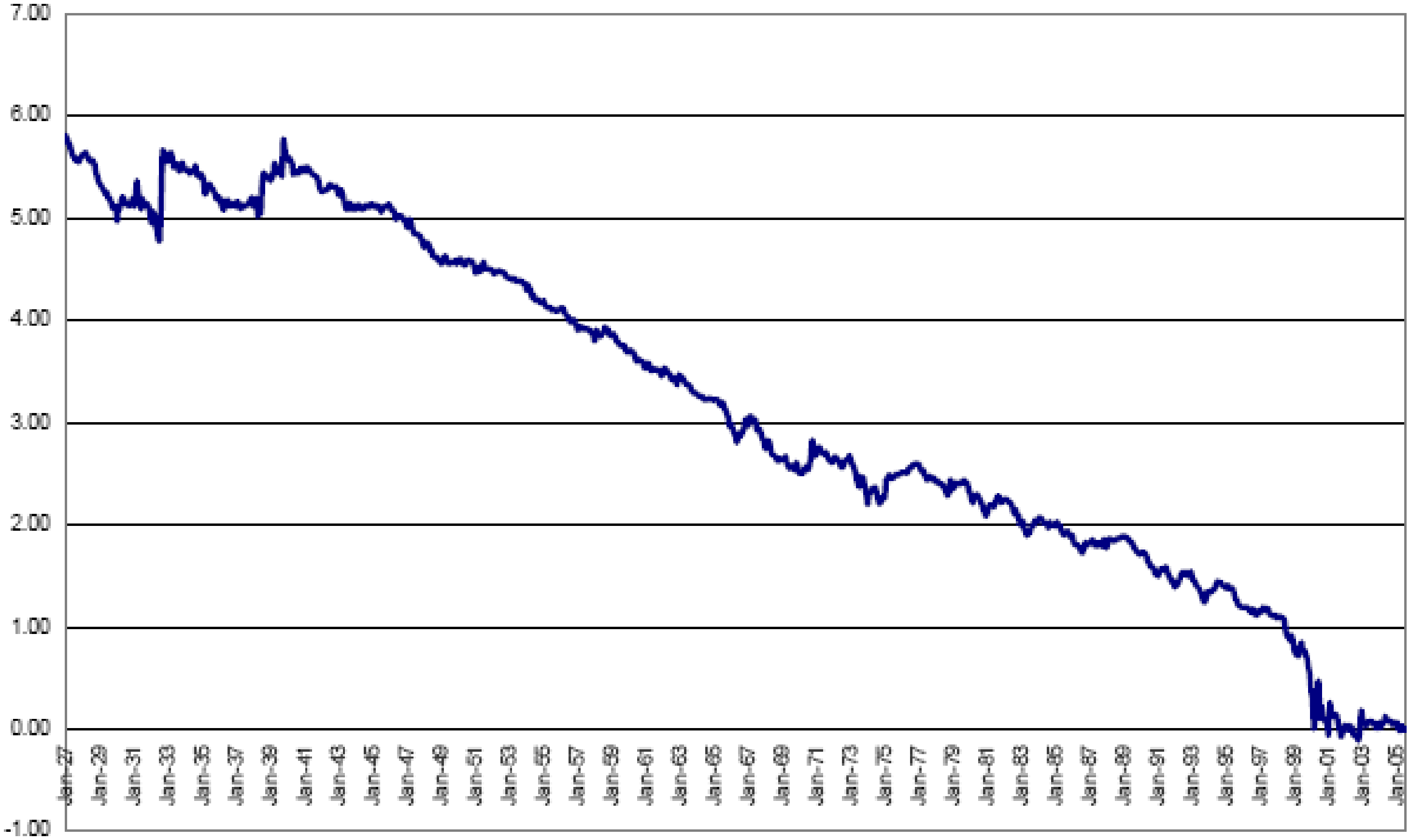
Loss of Momentum?

March 8, 2007

Has the focus of investors/traders (especially hedge funds) on stock return momentum, the persistence of outperformance and underperformance, killed the effect? In their March 2007 paper entitled "The Disappearance of Momentum", Soosung Hwang and Alexandre Rubesam investigate trends in the momentum effect over a long period. Their baseline analysis examines sets of ten momentum-ranked portfolios formed on past five-month returns and held for six months, with an intervening month skipped. Using monthly return data for a large number of individual NYSE, AMEX and Nasdaq stocks over the period July 1926 through December 2005, *they conclude that:*

- Over the entire sample, the average monthly momentum effect (return on top 10% minus return on bottom 10%) is +0.92%. However, on a risk-adjusted basis, momentum returns are significant in only four or five of 16 adjacent five-year intervals.
- There are major breaks in the momentum effect in 1939 and 2000. The effect is strong in the middle interval (1939-2000), but much weaker before 1939 and after 2000. Since 2000, the momentum effect alpha is negative on average, and about 70% of the return distribution is negative. An investor initiating a momentum strategy at the beginning of 2000 would have accumulated no profit through June 2005.
- The disappearance of the momentum effect since 2000 suggests that its discovery for 1939-2000 could be an artifact of data snooping bias.
- Results are robust to portfolio variations (based on firm size or NYSE stocks only), formation periods and holding periods.

The following chart, taken from the paper, shows the cumulative profit of the baseline momentum strategy per $1.00 invested long, according to strategy initiation date. Strategy portfolios are long the top 10% of stocks and short the bottom 10% based on five-month past returns. Portfolios are formed monthly and held for six months. For example, an investor initiating the strategy in the middle of the 1980s (the late 1990s) would have earned about $2.00 ($1.00) for each $1.00 in the original long position. If the momentum effect were reliable in all intervals, then the cumulative profit should be consistently higher for earlier start dates — the graph should decline steadily from the earliest start date to the latest. The chart shows that momentum effect profits: (1) did not reliably accumulate during 1927-1939: (2) accumulated with substantial reliability during 1939-2000; and, (3) are non-existent since 2000.



In summary, *the stock return momentum effect wasn't there, then it was there for a long time, and now it's gone.*

Originally published at http://www.cxoadvisory.com/1158/momentum-investing/loss-of-momentum/ on March 8, 2007.

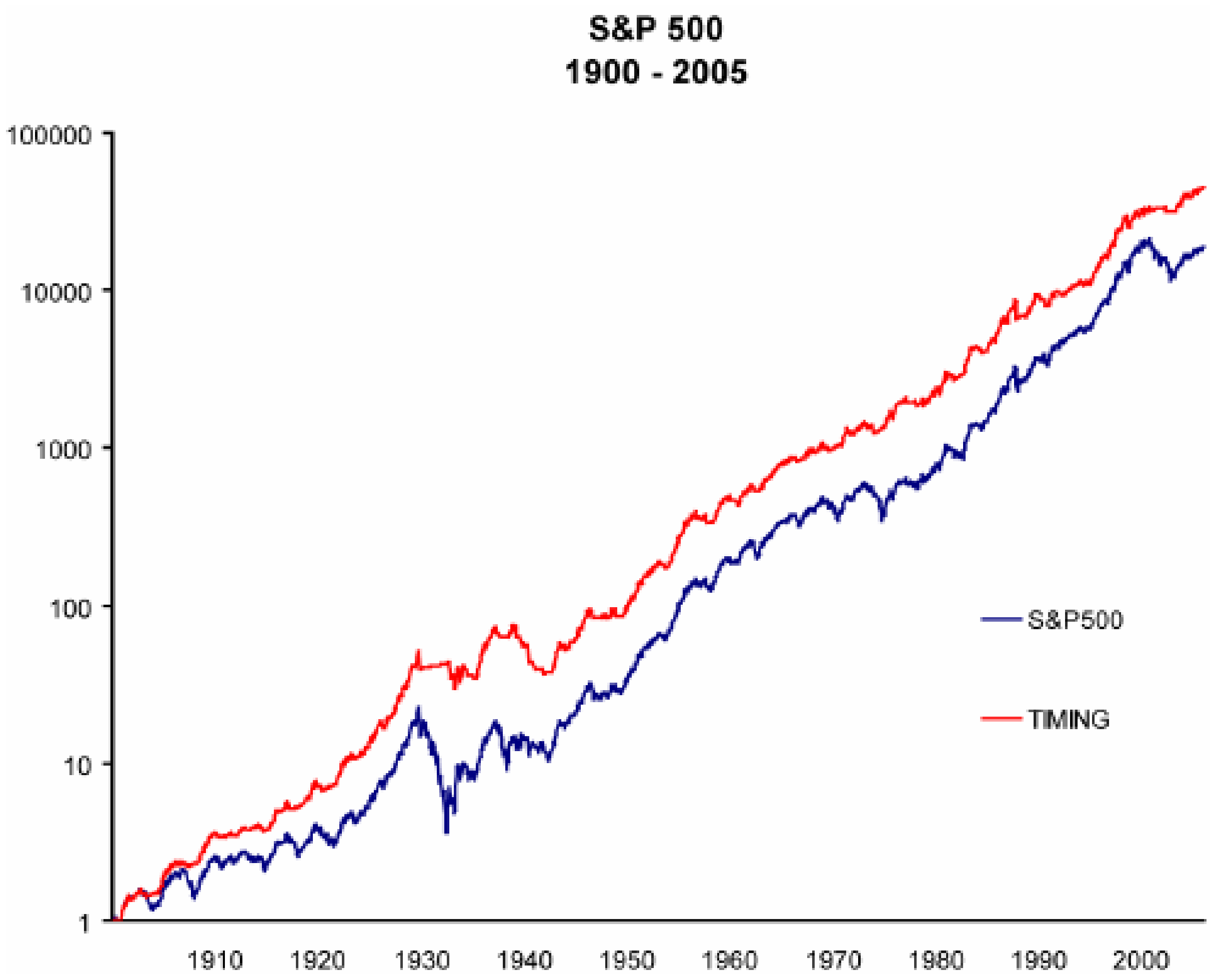
Long-Term Outperformance from Trends Defined by Moving Averages

February 15, 2007

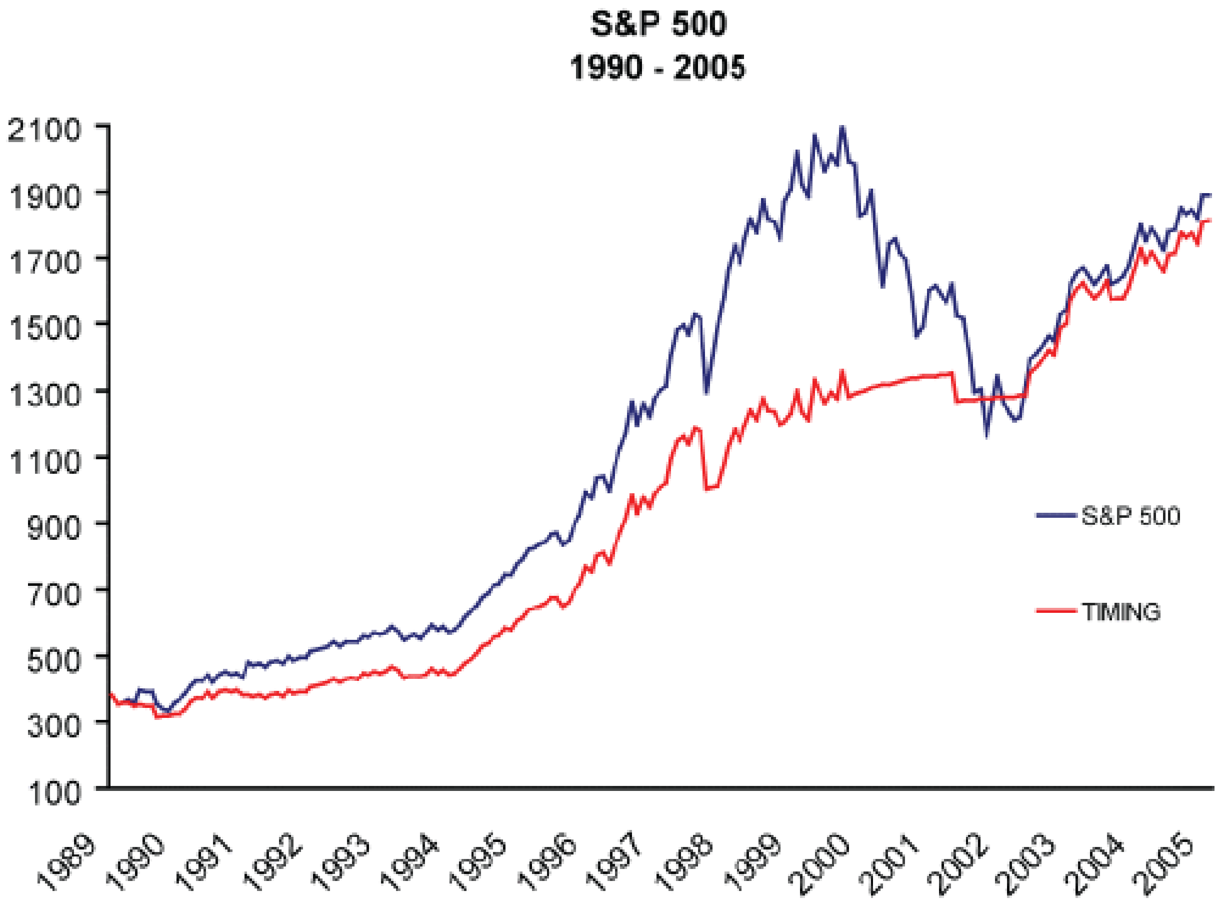
Does trading based on simple moving average crossovers outperform? In his November 2006 paper entitled "A Quantitative Approach to Tactical Asset Allocation", Mebane Faber presents a simple moving-average timing model that improves the risk-adjusted returns across various asset classes (represented, for example, by the S&P 500 index, the Morgan Stanley Capital International Developed Markets Index, the Goldman Sachs Commodity Index, the National Association of Real Estate Investment Trusts index and 10-Year Treasury notes). Using a model that mechanically buys (sells) an index when it crosses above (below) its 10-month simple moving average, *he shows that:*

- Applied to the S&P 500 index over 1900-2005, the model produces a 10.66% compound annual growth rate, compared to 9.75% for buy-and-hold. The timing model is less volatile than buy-and-hold. The model underperforms the index in about 40% of all years but avoids the worst bear markets. (See the first chart below.)
- Simple moving average periods of eight, 12 and 14 months produce similar results over 1900-2005.
- Over 1990-2005, the timing model slightly underperforms buy-and-hold based on raw returns, but suffers far less volatility. (See the second chart below.)
- Over the period 1972-2005, the timing model improves raw (risk-adjusted) returns for about 70% (90%) of 20 other indexes across asset classes.
- A straightforward application of the timing model across asset classes generates equity-like returns with bond-like volatility and drawdown, and over 30 consecutive years of positive performance. It modestly outperforms a simple equal-weighted asset allocation approach (and both beat buy-and-hold). A leveraged timing model substantially increases returns, at the cost of higher volatility.
- The timing model generates on average less than one round-trip trade per asset class per year, but taxes would still cut into the model's advantage over buy-and-hold unless trading in a tax-deferred account.

The following chart, taken from the paper, compares on a log scale the results of the simple moving average timing model and a buy-and-hold approach for the S&P 500 index (including dividends) over the period 1900-2005. The timing model avoids much of the drawdowns of the significant bear markets of the 1930s and 2000s.



The next chart, also from the paper, compares on a linear scale the results of the simple moving average timing model and a buy-and-hold approach for the S&P 500 index (including dividends) over the period 1990-2005. The model slightly underperforms based on raw returns, but has a much lower volatility. Note that the trend following model, while avoiding most of the 2000-2002 bear market, underperforms during the preceding strong bull market. Results suggest that trend-following may have been stronger prior to 1990 than after.



In summary, *this simple moving average trend-following model is a risk-reduction technique that signals when to be long a risky asset class with potential upside, and when to be sitting in cash.*

This is a very long horizon trading strategy, better suited to a tax-deferred account.

Originally published at http://www.cxoadvisory.com/1115/technical-trading/long-term-outperformance-from-trends-defined-by-moving-averages/ on February 15, 2007.

Follow the Leaders to Capture Short-term Abnormal Returns

January 11, 2007

Do investors/traders taking cues from the trades of top performers produce the momentum effect? In his December 2006 paper entitled "Follow the Leader: Peer Effects in Mutual Fund Portfolio Decisions", Lukasz Pomorski investigates whether actively managed equity mutual funds tend to follow the stock trading leads of outperforming peers as the picks become known via the media and quarterly filings. He defines outperforming (leader) funds in two ways: (1) funds with alphas in the top 5% over the past two years, and (2) funds on the *Forbes* Honor Roll (high media exposure). He calculates overall leader activity in a stock based only on trades by leader funds with a position in the stock. Using mutual fund holdings and performance data for 1980-2003 (96 quarters), *he finds that:*

- Leader funds (ranging from 13 to about 100 over the sample period) average twice the monthly returns of the remaining funds, with average alpha of about 1.5% per month. The *Forbes* Honor Roll funds average only 61% turnover, compared to over 100% for the typical fund.
- Other funds do mimic the trading of leaders, amplifying leader buys of a given stock by 15-30% in the following quarter.
- Mimicking behavior concentrates in stocks with the most informative leader trades: initiations and deletions, and trades in stocks with low market capitalization, little analysts coverage or high idiosyncratic volatility.
- Funds with below-median alphas react to leader trades about twice as strongly as funds with above-median alphas. The best funds do not mimic.
- A zero-cost value-weighted portfolio, long in stocks likely to be bought and short in stocks likely to be sold
  by mimickers, generates average returns (and alpha) of about 0.35% per month during the quarter after the leaders trade, with a relatively low monthly standard deviation of 2.3%. Results are statistically and economically significant.
- Neither stock price momentum nor stock fundamentals (news) explain this "follow the leader" trading behavior.

The author notes that quarterly mutual fund data probably understate the amount of mimicking that occurs across all timeframes and all market participants.

In summary, *mimicking the most informative actions of outperforming investors/traders reliably generates abnormal short-term returns. Such behavior may explain some of the momentum effect.*

Originally published at http://www.cxoadvisory.com/1067/mutual-hedge-funds/follow-the-leaders-to-capture-short-term-abnormal-returns/ on January 11, 2007.

Selling Too Soon, and Holding on Hope?

November 29, 2006

Do investors really sell winners and hold losers, thereby helping the market beat them? In other words, are they reluctant to admit mistakes? In their November 2006 paper entitled "Is the Aggregate Investor Reluctant to Realize Losses? Evidence from Taiwan", Brad Barber, Yi-Tsung Lee, Yu-Jane Liu and Terrance Odean investigate whether the average investor exhibits the disposition effect, the tendency to sell winning investments at a faster rate than losing investments. Using data for all trades on the Taiwan Stock Exchange during 1995-1999 (over one billion trades by nearly four million traders), *they conclude that:*

- Investors in the Taiwanese stock market are about twice more likely to sell a winning stock position than a losing stock position, and 84% of them sell winners at a faster rate than losers.
- Individuals, corporations, and dealers are reluctant to realize losses, while mutual funds and foreigners are not.
- Short sellers are also reluctant to realize losses.
- Men and women exhibit about the same level of reluctance to realize losses.
- The tendency to sell winners (losers) decreases (increases) after stocks go up, and increases (decreases) after stocks go down. However, because the increase in winning positions dominates the decrease in the tendency to sell winners, the overall willingness to sell increases following market advances.
- The disposition effect does not produce momentum in Taiwanese stock returns, perhaps because the effect of investors chasing performance offsets any effect of their preference to sell winners.

The following table, excerpted from the paper, shows Proportion of Gains Realized (PGR) and Proportion of Losses Realized (PLR) by investor type for the entire five-year sample, and calculates whether selling winners dominates selling losers based on both value of trades and number of trades. It shows that individual investors and dealers are most prone to sell winners rather than losers. It also shows that foreigners are more likely to sell losers than winners.

	Individual Investors	Corporate	Foreigners	Dealers	Mutual Funds	All Investors
Number of Investors	3,064,955	13,045	1,483	81	248	3,079,829
Mean PGR and PLR across Investors						
% Gains Realized: PGR = RG/(PG+RG)	9.43	5.01	1.00	7.33	1.49	9.40
% Losses Realized: PLR = RL/(PL+RL)	2.33	1.17	1.15	2.58	1.75	2.32
PGR – PLR	7.10***	3.84***	-0.15	4.75***	-0.26**	7.08***
Percentage of Investors where PGR > PLR (calculated using values of trades)	84.4***	55.5***	32.2***	91.4***	30.6***	84.2***
Percentage of Investors where PGR > PLR (calculated using numbers of trades)	85.7***	57.3***	36.9***	93.8***	55.2	85.5***

*** - reliably different from zero (or 50%) at the one percent significance level.

In summary, *data from Taiwan strongly supports the conjecture that investors avoid taking losses so that they do not have to admit mistakes.*

Investors may want to think about whether they are holdling losers on hope.

Originally published at http://www.cxoadvisory.com/1016/animal-spirits/selling-too-soon-and-holding-on-hope/ on November 29, 2006.

Momentum Strategies Sputtering?

August 23, 2006

How are momentum stock trading strategies doing these days? In their January 2006 paper entitled "The Vanishing Abnormal Returns of Momentum Strategies and 'Front-running' Momentum Strategies", Thomas Henker, Martin Martens and Robert Huynh examine the returns of various momentum trading strategies in general and during specific market conditions (rising or falling) over the period 1993-2004. They construct a series of self-financing portfolios (equal-weighted) for various holding periods by buying past winners and selling past losers based on various past performance (ranking) periods. Some strategies include a one-month gap between the ranking and holding periods. They repeat portfolio construction monthly over the sample period for each strategy, resulting in overlapping portfolios. Finally, they test "front-running" strategies that set momentum rankings five days before the ends of months rather than at month-ends. Using daily data to calculate monthly returns for a broad sample of stocks (with all distributions reinvested), *they find that:*

- Because of weak results during the bear market of the early 2000s, self-financing momentum strategies in general did not reliably generate significant returns across the entire 1993-2004 period.
- Momentum strategies work better during a rising market than during a falling market.
- Momentum strategy results are generally stronger and less volatile for the stocks of medium-sized and large firms than those of small firms.
- Momentum strategies work better for NYSE/AMEX stocks than for NASDAQ stocks.
- "Front-running" momentum strategies generally outperform month-end strategies because of lower volatilities, suggesting perturbations from month-end institutional trading. The "front-running" enhancement appears to be concentrated in small stocks.

In summary, *there are a lot of twists and turns to momentum strategy returns.* Momentum players should pay attention to the subtleties.

Originally published at http://www.cxoadvisory.com/867/momentum-investing/momentum-strategies-sputtering/ on August 23, 2006.

Combining Momentum and Value

May 25, 2006

Value and momentum are two very different equity investing styles, both with many adherents. Neither outperforms the overall market all the time. Is there some systematic way of combining these two approaches to enhance consistency of outperformance in global equity markets? In their March 2006 paper entitled "Generating Excess Returns through Global Industry Rotation", Geoffrey Loudon and John Okunev examine different investing styles (momentum, value, combination of value and momentum, and growth) to exploit cyclic industry returns, with the U. S. yield curve as the critical economic indicator. Using monthly global prices, dividends, earnings and returns data for 36 industries for 1973-2005, *they conclude that:*

- Industry leadership has varied considerably during 1973-2005 (see first table below), and industry effects may now be more important than country effects with respect to variability of global equity returns.
- The industries with the highest earnings yields outperform those with the lowest. However, value-focused strategies performed poorly in the 1990s.
- Industries with the highest growth rates outperform those with the lowest. However, growth has not worked well in the 2000s.
- The most effective momentum strategy focuses on industries with the highest 12-month trailing returns. However, momentum-focused strategies performed poorly in the 1970s and (so far) 2000s.
- When the U.S. yield curve is normal the top performing industries (average 15.2% return per year) are Tobacco, Water, Aerospace/Defense, Information Technology and Food & Drug Retailers, and the bottom industries (average 10.3% return per year) are Forestry/ Paper, Mining, Steel & Other Metals, Diversified Industries and Chemicals. The best (worst) investing strategy is momentum (value).
- When the yield curve is inverted the top performing industries (average 14.0% return per year) are Mining, Water, Tobacco, Oil and Gas and Forestry/Paper, and the bottom industries (average -17.2% return per year) are Information Technology, Media & Photography, Household Goods, Autos and Software. The best (worst) investing strategy is value (momentum).
- Combining the industries with the best value and highest momentum significantly enhances returns overall and for all decades except the 1980s.

The following table, taken from the paper, shows that the top-performing and bottom-performing industries vary considerably from decade to decade. In particular, 1990-1999 was a "momentum" decade.

	Industry	73-79 Av Return	Industry	80-89 Av Return	Industry	90-99 Av Return	Industry	00-05 Av Return
Top 4.	Aerospace/Defense	19.6	SPC&Oth. Finance	28.2	Software	32.8	Tobacco	22.3
	Oil & Gas	12.4	Water	27	Inf. Techn.Hardw.	23.3	Mining	18.7
	Mining	12.4	Tobacco	26.4	Telecom Serv.	16.1	Oil & Gas	14.5
	Gas Distribution	9.1	Banks	23.3	Pharmaceuticals	16.1	Water	13.6
Bottom 4	Media & Photography	-4.6	Software	11.2	Steel&Oth. Metals	-3.6	Inf. Techn.Hardw.	-15.2
	Retail,General	-4.1	Aerospace/Defense	11.8	Cons&Bldg Mat.	-0.1	Software	-14.9
	Per. Care&Hshld	-4	Mining	11.8	Transport	0.3	Telecom Serv.	-12.1
	Beverages	-2.5	Inf. Techn.Hardw.	14	Eng&Machinery	2.4	Media & Photography	-7.4

The next table, also taken from the paper, compares the performances of 16 groups of industries defined by both momentum and value characteristics. It shows that cheap, high-momentum equities outperform, with the best group beating the worst by more than 12% per year.

MOMENTUM	VALUE	Q1 Expensive	Q2	Q3	Q4 Cheap	Return Difference
Q1 (Loser quartile)	Average Return	7.20	8.60	9.90	12.90	5.80
	Std	18.80	16.90	17.30	15.70	15.70
	T value					2.10**
Q2	Average Return	6.80	11.90	11.10	13.40	6.60
	Std	17.40	16.90	15.00	14.70	14.70
	T value					2.57**
Q3	Average Return	10.60	14.90	12.10	15.00	4.50
	Std	16.20	15.20	14.40	15.10	12.50
	T value					2.05*
Q4 (winner quartile)	Average Return	16.40	15.40	13.90	19.50	3.10
	Std	16.80	16.10	15.60	16.90	17.40
	T value					1.00
	Return Difference	9.30	6.90	4.00	6.60	12.30
	Std	17.40	15.30	15.60	16.20	15.50
	T value	3.05**	2.6**	1.50	2.33**	4.8**

* significant at 5%

** significant at 1%

In summary, *investors can enhance returns by combining value and momentum styles, leaning toward momentum when the yield curve is normal and value when the yield curve is inverted.*

This research should be of particular interest to investors who use industry-focused Exchange Traded Funds.

Originally published at http://www.cxoadvisory.com/755/value-premium/combining-momentum-and-value/ on May 25, 2006.

Classic Research: Embrace Risk, But Take Profits

February 15, 2006

We have selected for retrospective review a few all-time “best selling” research papers of the past few years from the General Financial Markets category of the Social Science Research Network (SSRN). Here we summarize the February 1999 paper entitled “Daily Momentum And Contrarian Behavior Of Index Fund Investors” (download count almost 1,900) by William Goetzmann and Massimo Massa. The authors investigate the existence and profitability of momentum and contrarian behaviors for stock index trading. They classify return momentum investors (trend followers) as those who buy (sell) when the market rises (drops) in the previous trading session, and return contrarian investors as “profit takers” who sell (buy) when the market rises (drops). They also examine investor response to changes in market volatility, defining both volatility momentum traders (risk chasers) and volatility contrarian traders (risk avoiders). Using daily activity records for 91,000 accounts trading an S&P 500 index during 1997 and 1998, *the authors find that:*

- Passive index fund holders trade infrequently, typically once a year, although some accounts are quite active. There are no calendar effects (end-of-year, end-of-month…) evident in the trading activity.
- About 25% all accounts are return contrarians, and 12% are return momentum traders. Among frequent traders, however, more than 50% are return momentum players. There is a little bit more risk (volatility) chasing than risk avoiding.
- Return contrarians (profit takers) tend to earn significantly higher profits than the rest of the market.
- Risk chasers (volatility momentum traders) tend to earn higher profits than risk avoiders.

The authors also explore the impacts of momentum and contrarian investor behaviors on price, with focus on times when these behaviors are most dramatically opposed.

In summary, *traders can outperform by entering positions when volatility spikes and then taking profits quickly.*

Originally published at http://www.cxoadvisory.com/667/volatility-effects/classic-research-embrace-risk-but-take-profits/ on February 15, 2006.

Buying on Impulse (Change in Momentum)

September 14, 2005

In their September 2005 paper entitled "Acceleration Strategies", Eric Gettleman and Joseph Marks examine the change in six-month stock price momentum (a second derivative of price with respect to time, which the authors call "acceleration") for individual companies as a potential indicator of future performance. Does increasing (decreasing) stock price momentum indicate commensurate relative outperformance (underperformance)? Based on monthly data spanning 1926-2003, *they conclude that:*

- Stocks with extremely high price acceleration outperform stocks with extremely low price acceleration by 6.15% when controlled only for momentum and 4.5% when controlled for other possible effects.
- Trading on both stock price momentum and acceleration extends the outperformance of simple momentum strategies by about 3% over a six-month holding period, with a higher Sharpe ratio.
- These results are consistent with the behavioral view that investors react only gradually to firm-specific information.

In summary, *focusing on stocks with both high six-month momentum and rapidly increasing six-month momentum offers significant excess returns.*

A more precise analogy with physics suggests that "impulse" is more appropriate than "acceleration" as a name for this effect.

A reader asked: "Please help me understand the calculation of 'acceleration.'"

Response:

> In general (from physics), velocity is the change in position (first derivative of position), and acceleration is the change of velocity (second derivative of position). Similarly (again from physics), momentum is mass times velocity, and impulse is the derivative of momentum.
>
> The author of the reviewed paper uses the term acceleration to mean the change in stock price momentum. The return of a stock or fund over some past interval of time (say six months) is a measure of its momentum. The change in this measure of momentum over some interval of time (say a month) is a measure of stock price acceleration.
>
> For example, assume you measure momentum for a set of stocks or funds monthly as 6-

month past return. This month, you find that a specific stock has advanced 30% over the prior 6 months, so its momentum is 30%. Next month, you roll your data by a month and find that the same stock has a revised momentum of 35%. Its momentum is accelerating. Conversely if you find the momentum of a stock decreasing from month to month, its momentum is decelerating.

The study finds that stocks with high and accelerating momentum outperform those with high momentum only.

Originally published at http://www.cxoadvisory.com/492/momentum-investing/buying-on-impulse-change-in-momentum/ on September 14, 2005.

The Disposition Effect as a Driver of Momentum

August 1, 2005

In the February 2005 update to his paper entitled "The Disposition Effect and Under-reaction to News", Andrea Frazzini tests whether the "disposition effect" (the tendency of investors to sell stocks that have gone up, not down, in value since purchase) causes stock prices to under-react to bad news when most current holders face a capital loss and under-react to good news when most current holders face a capital gain. Using a database of the holdings of a large class of investors (mutual funds) to estimate reference prices for individual stocks, he ranks stocks according to unrealized capital gains/losses and correlates this ranking with response to corporate news and subsequent return. Based on data spanning 1980-2002, *he finds that:*

- Like ordinary investors, mutual fund managers tend to sell a higher proportion of their winners than their losers.
- Predictability of returns after news reports is strongest when the disposition effect indicates the biggest under-reaction (when unrealized capital gains/losses are extreme).
- Post-event drift is larger when the news and the unrealized capital gains/losses have the same sign, and the magnitude of the drift is directly related to the magnitude of unrealized stockholder capital gains/losses prior to the event date.
- Stocks with large unrealized capital gains (losses) tend to have higher (lower) subsequent returns. Event-driven strategies based on this effect yield monthly excess returns of about 1% after transaction costs.
- These results suggest that the disposition effect may drive both price and earnings momentum, and that past returns may be a noisy measure of the unrealized capital gains of stock holders. Positive (negative) news travels slowly in stocks with large capital gains (losses) as disposition effect trading dampens transmission of information, thus feeding return continuation.

In summary, *the disposition effect may serve as the bootstrap of momentum investing by retarding the impact of good (bad) news for stocks with large unrealized capital gains (losses).*

Originally published at http://www.cxoadvisory.com/416/momentum-investing/the-disposition-effect-as-a-driver-of-momentum/ on August 1, 2005.

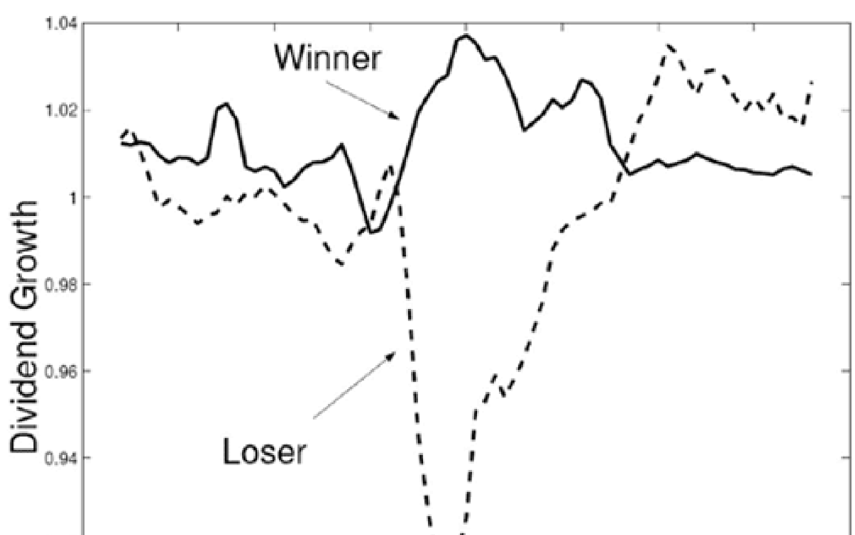
Momentum Investing: Surfing Waves in the Economy?

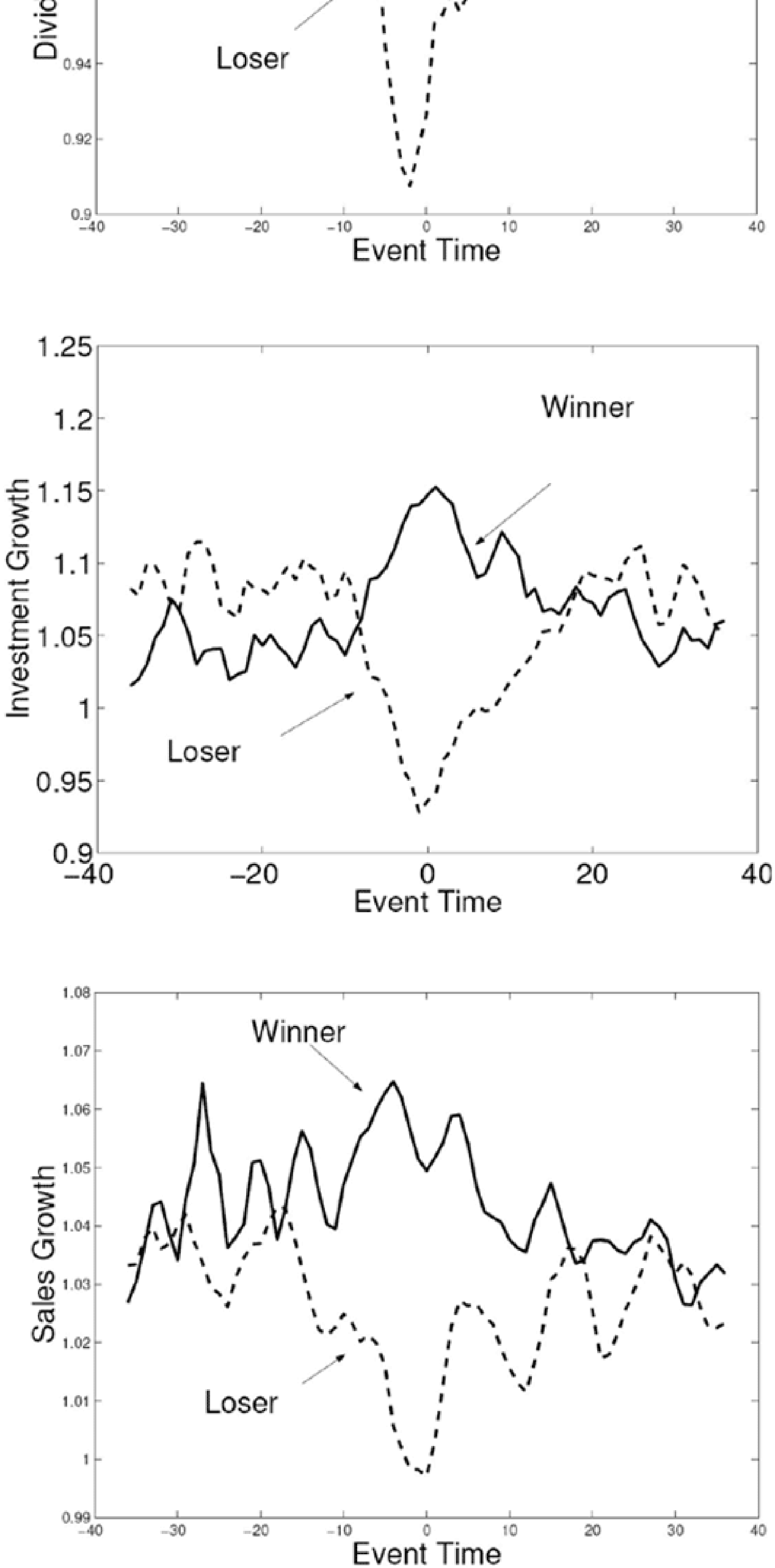
July 28, 2005

In their June 2005 paper entitled "Momentum Profits and Macroeconomic Risk", Laura Liu, Jerold Warner and Lu Zhang examine the connection between momentum returns and the overall economy, using the growth rate of industrial production as a proxy for the economic trend. They use monthly data for a large selection of common stocks listed on the NYSE, AMEX, and NASDAQ from January 1960 to December 2001 to construct ten equally weighted momentum portfolios, ranking on past six-month returns and holding for six subsequent months. *They find that:*

- The average winner-minus-loser (top decile minus bottom decile) excess return is 0.85% per month.
- Winning portfolios are more sensitive to the industrial production growth rate than are losing portfolios. In other words, they are at greater risk with respect to changes in the overall economy. This condition is temporary and asymmetric, driven by the high sensitivity of stocks in the highest deciles.
- This difference in sensitivity is economically significant, accounting for up to 40% of excess returns for momentum investing.
- Winners have temporarily higher average future growth rates of dividends, capital investment and sales than losers. At the month of portfolio formation, the growth-rate differentials between winners and losers are sizable: 11% in quarterly dividend growth, 22% in quarterly capital investment growth and 5% in quarterly sales growth. The duration of these growth differentials roughly matches that of the momentum returns.

The following charts, extracted from the paper, illustrate the differentials between winner and loser portfolios noted in the last bullet above. Growth rates are quarterly, and event times are in months. All growth rates show reversion for both winner and loser portfolios.





In summary, *momentum investing works, driven partly by reward for the risk of the unusual but transitory sensitivity of high-momentum stocks to overall economic growth.*

Originally published at http://www.cxoadvisory.com/405/momentum-investing/momentum-investing-surfing-waves-in-the-economy/ on July 28, 2005.

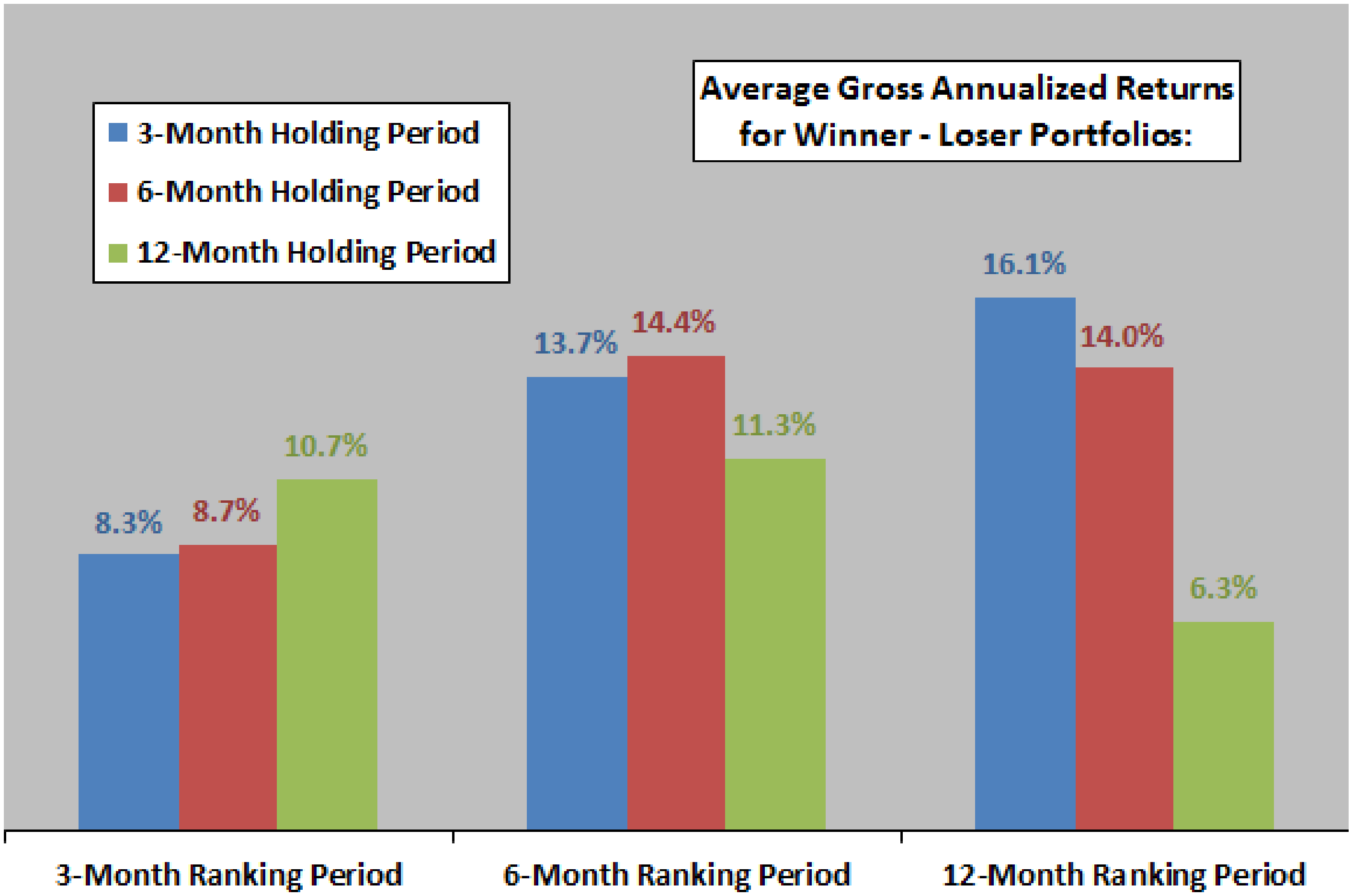
Why Momentum Investing Works?

July 19, 2005

In their July 2005 paper entitled "Momentum Profits and Non-Normality Risks", Ana-Maria Fuertes, Joelle Miffre and Wooi Hou Tan examine the distributions of returns for nine momentum investing strategies as they attempt to explain why the resultant portfolios outperform. These nine strategies consist of overlapping portfolios formed monthly that are long (short) the equally weighted tenth of stocks with the highest (lowest) return over the past 3, 6 or 12 months and held for the next 3, 6 or 12 months. Using monthly data for all NYSE, AMEX and NASDAQ stocks priced over $5 during February 1973 through August 2004, *they find that:*

- All nine momentum strategies they examine show significant performance advantages for past winners over past losers (see chart below).
- The standard deviations of the past winner portfolios is consistently just smaller than those for past losers, so reward-for-volatility risk does not explain the outperformance of past winners.
- The distributions of winner returns consistently deviate more from normal than do loser returns, exhibiting a more negative skewness (the distribution curve tilts to the right) and kurtosis (flattened, with fat tails). Rewards for these distribution abnormalities may partially explain why momentum strategies work.
- Momentum portfolios tend to follow the rhythms of the business cycle, incorporating more risk (higher beta and more negative skewness) during economic expansions than during recessions.
- Efficient market theory still cannot explain fully the outperformance of momentum investing. Illiquidity and transaction costs may be part of the puzzle. The alternative view of behavioral economists, that momentum is a consequence of the market responding slowly to news, is still in play.

The following chart, constructed from data in the paper, summarizes gross annualized returns for all nine momentum strategy (winner minus loser) combinations based on ranking intervals of 3, 6 or 12 months and holding intervals of 3, 6 or 12 months. All portfolios generate considerably higher gross average returns for past winners than for past losers. Ranking based on a past performance period of 12 months and a holding period of three months produces the largest difference.



In summary, *momentum investing works, and abnormalities in the distribution of returns for momentum-driven portfolios may partly explain why.*

Note that accounting for trading frictions would materially reduce reported strategy returns.

Originally published at http://www.cxoadvisory.com/386/momentum-investing/why-momentum-investing-works/ on July 19, 2005.

Going with the Flows

May 8, 2005

In their May 2005 paper entitled "Asset Fire Sales (and Purchases) in Equity Markets", Joshua Coval and Erik Stafford examine the effects on stock prices of mutual funds forced to sell (buy) because of predictable outflows (inflows) of funds based on their past performance. Does such forced selling and buying present predictable opportunities for front-running? By studying mutual fund transactions caused by capital flows from 1980 to 2003, *they conclude that:*

- Funds in the bottom decile of capital flows typically hold about 25% fewer securities than the average fund. They are roughly twice as likely to sell, creating significant downward price pressure in the stocks held in common by such funds.
- Funds with large inflows tend to increase their existing positions, creating significant upward price pressure in the stocks held in common by such funds. Extreme inflows to mutual funds are much more common than extreme outflows.
- Flow-driven transactions by mutual funds are predictable based on their past performance and their reported holdings. The price effects last about two quarters, taking several more quarters to reverse.
- Flow-driven buying and selling by mutual funds is highly related to the momentum effect in equity returns. Stocks that mutual funds with poor past performance must sell tend to overlap with the stocks identified as good shorts by a momentum strategy.
- Investors who provide liquidity by trading against flow-driven transactions earn highly significant returns. An investment strategy that sells short stocks most likely to be involved in forced sales and buys ahead of anticipated forced purchases earns average annual excess returns of over 15%. Most of this excess comes from front-running inflows.

In summary, *front-running the predictable effects of unusual mutual fund inflows and outflows on stocks held in common offers significant excess returns.*

Originally published at http://www.cxoadvisory.com/317/mutual-hedge-funds/going-with-the-flows/ on May 8, 2005.