Columbine White Paper

Factor Success Rates: Will Success Spoil The Quants' Game?

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ABSTRACT

We pose and address these two questions:

First, is there any evidence that the utility of quantitative return factors is decreasing over time? It turns out there is such evidence. We address the magnitude of erosion observed and its possible causes.

Second, if factor utility is eroding, what are the future prospects for multifactor quantitative models that are built from such factors? We find some evidence that erosion of success has slowed and likely stabilized at current levels, suggesting continued usefulness of factor-based quantitative models. However, future alphas may not be as large as in the past.

A sobering conclusion from these studies is that at current levels—and especially if erosion continues—simple, common linear factor models may suffer in the future in competition with more innovative models exploiting new anomalies and/or nonlinearities in existing anomalies.

BACKGROUND

The past decades have seen a dramatic increase in the use of quantitative investment models. The profession's view of such tools moved from one of outright rejection (they clearly violate market efficiency assumptions), to grudging acceptance, to enthusiastic embrace. Formerly skeptical academics, who started their careers as doctrinaire efficient market believers, are now highly compensated "financial engineers" for hedge funds. Instead of being eyed with suspicion, quantitative models are now a standard part of the investment professional's repertoire.

Which raises the question, will this success spoil the game for the quants? A central tenet of market theory states that any return opportunity that gets widely recognized should be arbitraged away. As quantitative investing becomes more widespread, are the anomalies and inefficiencies it exploits also disappearing, setting the stage for the downfall of quantitative model-driven investing? With this study we will try to supply an answer to that question, at least as far as our own models are concerned.

STUDY DESIGN

Using optimized multifactor models like our own Combo Model to address the effectiveness of quantitative tools across time is problematic. Returns from optimal models are necessarily biased upward in their fitting periods. In addition, because they emphasize the best performing factor inputs, it is possible that optimized model performance, even out of sample, may mask a deterioration in effectiveness of many factors.

To avoid this potential distortion we chose to address the effectiveness of quantitative techniques by focusing on simple individual return factors. For the most part each of these focuses on a single anomaly or stock characteristic, providing a non-optimization biased measure of quantitative effectiveness in isolation.

The factors we used for the analysis are the ten building blocks of our own proprietary multifactor models – five valuation-based factors and five momentum- or growth-based factors:

Valuation Factors

- BV – book value to price
- CF – cash flow to price
- REP – reported (trailing) earnings to price
- FEP – estimated (forward) earnings to price
- DY – dividend yield

Momentum Factors

- PM – price momentum (Columbine Alpha Factor)
- EC – short-term earnings change
- EG – long-term earnings growth
- ER – estimate revision
- ES – earnings surprise

Definitions for each of these factor models can be found on the Columbine Capital web site: http://www.columbinecap.com/services/factor.asp

Database

Our database for the analysis is our *Columbine 1500 Universe*, consisting of 1,500 liquid, institutional-quality stocks, redefined every year. The *Columbine 1500* includes all the stocks of the *S&P 500 Composite Index* each year, allowing us to test in a big-cap subset of the database. Our data extends back to 1971 for most factors, but only to 1990 for the three estimate-based factors. We tested the effectiveness of all ten factors together, as valuation and growth subsets, and then each factor separately.

Measuring Factor Success

Factor returns are tricky to use in evaluating any potential decline in the effectiveness of factors over time. Factor return performance is necessarily affected by the returns to equities in general, and even an analysis of the alpha generated by factors may be contaminated by changes in volatility and other market effects.

Instead of the magnitude of factor return or alpha, we utilize a simple bounded pass/fail measure of factor effectiveness: did it generate a positive 1st minus 10th decile return spread, observed monthly? For individual factors we can then compute the fraction of trailing twelve-month observations when it was successful, and for groupings of multiple factors we can compute the fraction of factors that were successful in a given month. In either case we refer to this fraction as the *factor success rate.*

As expected, the monthly factor success rate is positively correlated with the monthly top-bottom decile return spread generated by all of Columbine's multifactor models. For the Combo Model, for example, that correlation is +0.6.

Theoretically, a success rate of 50% represents the baseline for generating positive alpha from a multifactor model. Strong performance from one or two of the successful factors could overcome the failure of the majority, but as the rate drops lower than 50% the chance of producing a positive alpha drops off sharply. Changes to these factor success rates across time may give us at least a partial picture of any trends

Figure 1. Average Factor Success Rate by Month

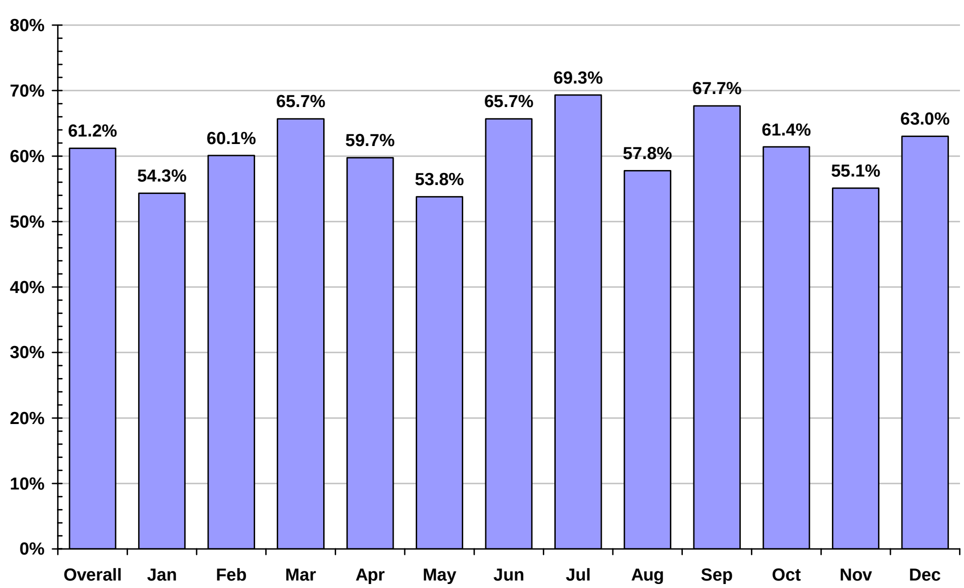
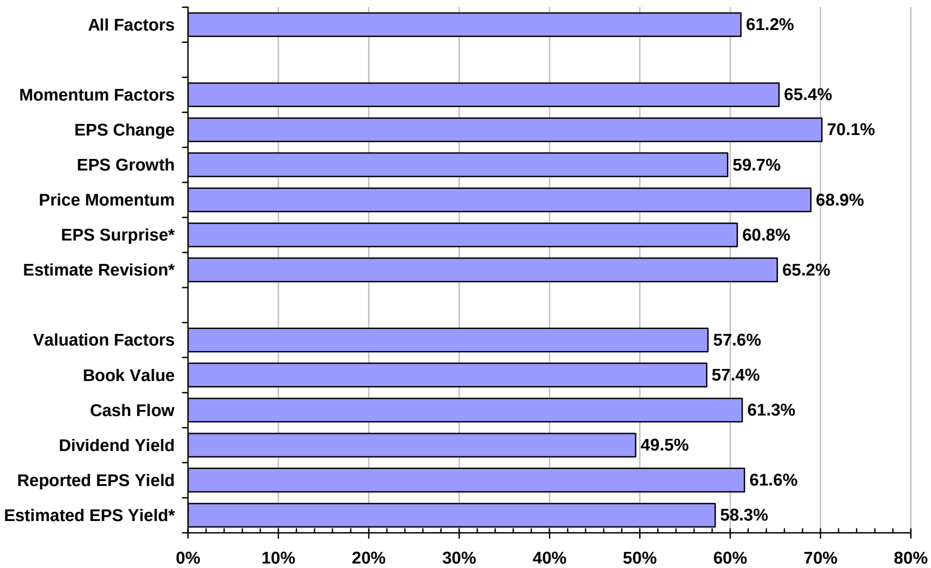


Figure 2. Average Success Rate by Factor



in the effectiveness of the building blocks of quantitative investing.

FIRST IMPRESSIONS OF THE DATA

Figure 1 reports the overall average rate of factor success from 1971 through 2006, and breaks out the success rate by calendar month. While some seasonal variation is suggested, we do not believe the month to month differences are statistically meaningful.

Figure 2 illustrates the average success rate by factor and for the momentum and valuation factor groupings. In general, the success rates for the momentum (growth) factors are higher than for the valuation factors. This is consistent with our findings of style performance, as reported in Brush, "Value and Growth, Theory and Practice," *Journal of Portfolio Management*, 2007. Month-by-month success rates for all factors are reported in **Appendix I**.

Given the mean success rate for all ten of the factors of 61.2%, our expectation for any given month should be that around two-thirds of the return factors will be successful. However, the standard deviation of the monthly series is 23%, so monthly success rates ranging anywhere from 39% to 85% will be typical. The practitioner's concern, however, really is not the typical month's factor success rate, but the *atypical*. How often will factor success rates be so low that they adversely affect the performance of multifactor alpha-forecasting models?

Figure 3 plots the distribution of the monthly success rate levels over the entire period of the study in 10% increments. Each bar represents the number of months in which the overall factor success rate was in a particular range. The graph shows that our statistical expectation matches the observed reality—the majority of observations fall in the ranges between 41% and 90%. We chose a factor success rate of 40% as our threshold for declaring that a given month has experienced a *factor failure* if the success rate is at or below that level.

From 1971 through 2006 there were 77 months with a 40% or lower success rate, about 18% of the 420 months in the study. There were even five months when *none* of the factors succeeded. The table in **Appendix II** provides a historical context for these more extreme occurrences. To create the table we extracted every month with a success rate of 40% or lower from the historical record. The table simply reports these months and their success rates in chronological order, and breaks out the frequency of these factor failures by calendar month and year.

Looking at the history of these factor failures, a couple of points stand out. First, there are very few clusters of two consecutive extreme low success months. The most

Figure 3. Factor Success Rate Distribution

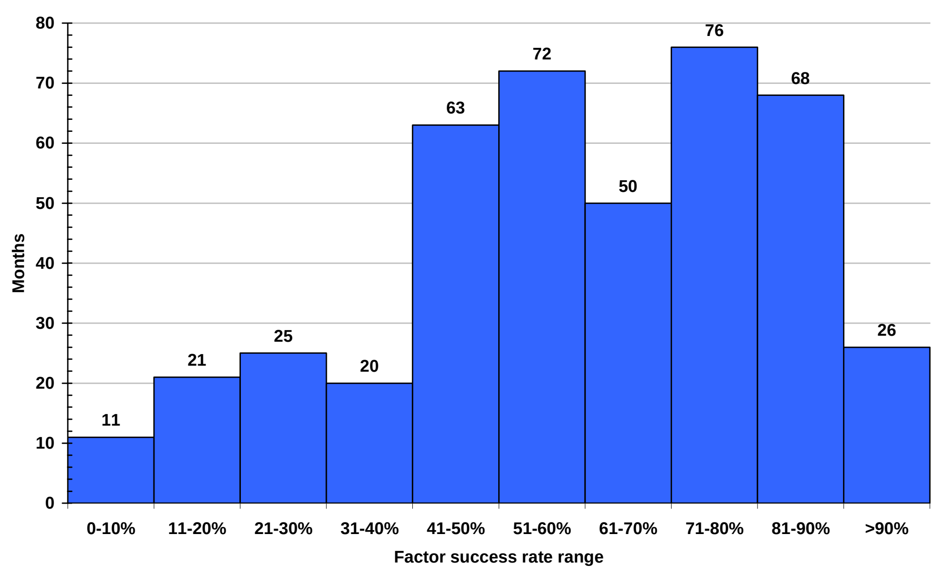
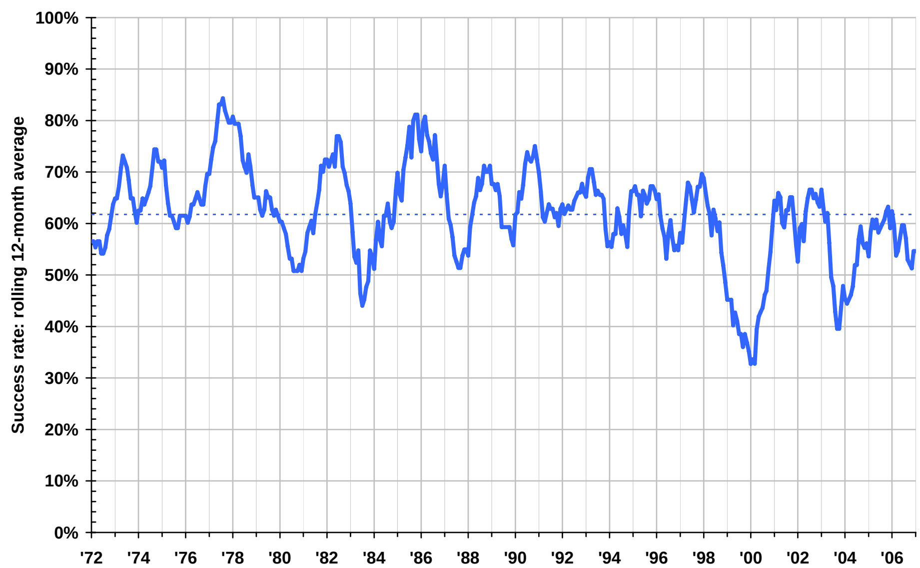


Figure 4. Overall Factor Success Rate



common such pairing appears to be October-November, with April-May running second. These four months also are in the top half of the calendar month frequency distribution with high numbers of factor failure events. January is high on that list as well. We have omitted the January price momentum spreads, so this would seem to indicate that the month is troublesome for other factors as well (Earnings Growth, for example).

Second, the prevalence of these low success incidents seems to be increasing. There were only four such events in the entire decade of the 1970s, and eighteen in the 80s. But we experienced thirty-six factor failure events in the 90s, and in the five years since the beginning of the 21st century we already have had nineteen factor failure incidents, including two of the October-November clusters. This pattern adds credence to the idea that factor effectiveness may be deteriorating over time. To assess that we need to look at the time series of the monthly factor success rates.

TIME SERIES ANALYSIS

Figure 4 represents a rolling twelve-month average of the monthly overall factor success rates, *i.e.,* the fractions of factors that were successful each month. The historical mean rate of 61.2% is plotted as a dashed line. There have been some fairly wide swings in the rate over the years, but the lowest recorded excursion took place at the beginning of 2000, when the trailing-twelve month success rate dropped to about 33%. The second-lowest excursion occurred in late 2003. Since then the rate has returned to a level close to the historical mean, but has not reached any of the high levels observed in the 70s or early 80s.

At first glance the raw success rate data of **Figure 4** suggests that, considering all ten factors, there is a slow but erratic downward trend in factor success rate over time. Fitting a simple linear time trendline to the overall series (**Figure 5)** makes concrete what your eye suggests. Based on the raw data the success rate appears to be dropping by a few tenths of a percent annually.

Figures 6 and **7** plot the same information for the momentum factors and for the valuation factors respectively. In both cases the same pattern emerges—a gradual but jumpy decline in the factor success rate over time. The momentum factors start from a higher success level with a mean rate of 65.4%, compared to the valuation factors' mean rate of 57.6%, but their decline appears to be more pronounced than valuation's. Both series have approximately the same standard deviation: 33%.

Charts of the rolling twelve-month average success rate for each of the individual factors are presented in **Appendix III.**

Figure 5. Overall Factor Success Rate with Trendline

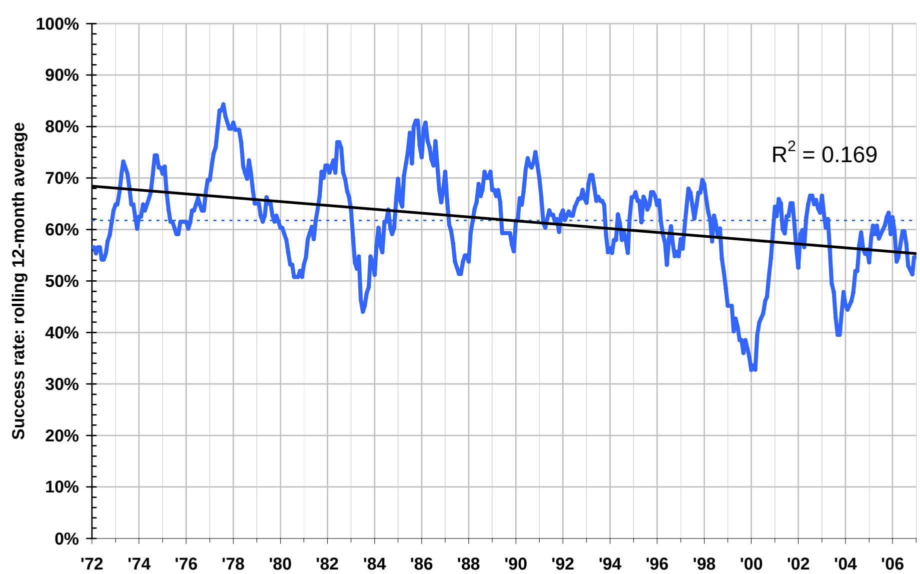


Figure 6. Momentum Factors Success Rate with Trendline

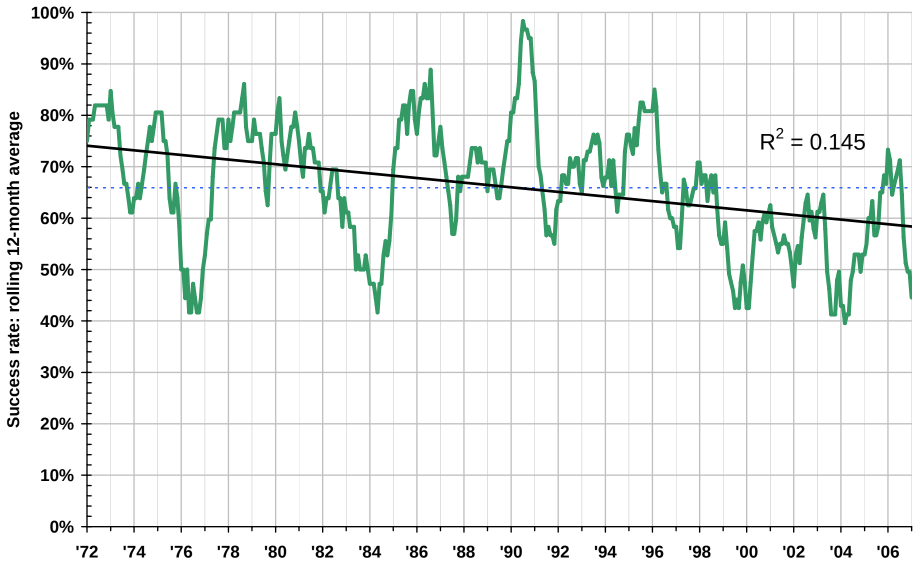
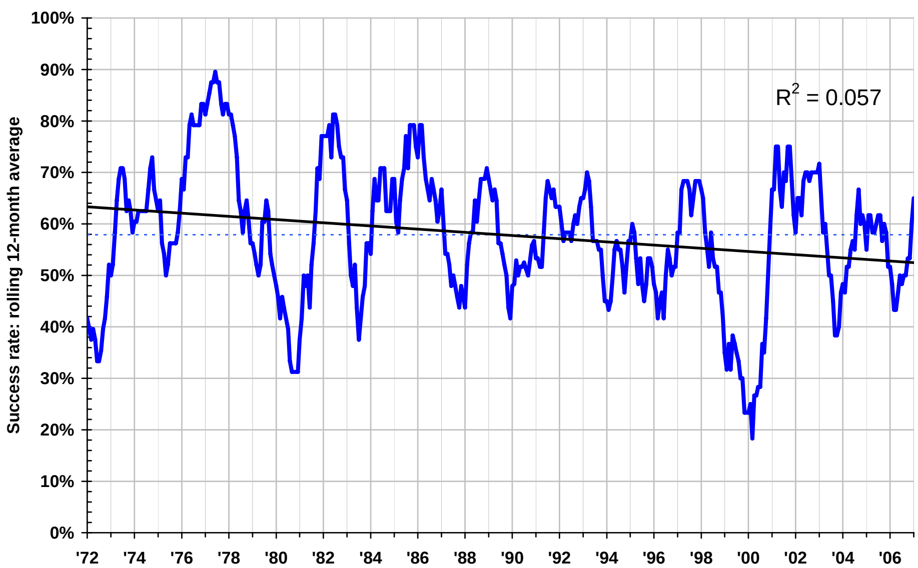


Figure 7. Valuation Factors Success Rate with Trendline



The Dot.Com Era

The dot.com era of the 1990s can be viewed as a severe unusual distortion revealing previously unseen time and style dynamics in factor failure. Although returns from momentum and valuation factors are normally negatively correlated, the dot.com years ushered in an extended period of positive correlation in factor success rates for the two styles that only recently ended. **Figure 8** illustrates the rare simultaneous failure of both momentum and valuation factors (annual averages) at the height of the dot.com bubble in 1998 through 1999. (There was also a period of simultaneous factor success in the early 80s.) We speculate that the extreme of factor failure experienced in 1998 and 1999 was due to the alien influence of the "new economy" ideas driving equity pricing, which swamped more usual effects.

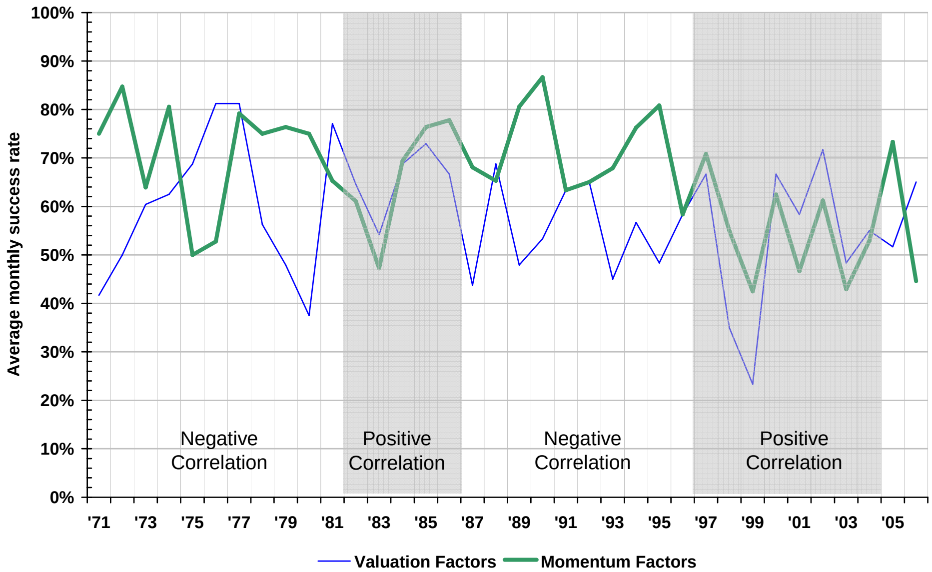
The reaction to this initial distortion caused a return to positive effectiveness almost repairing the distortion damage as factors bounced back to strong simultaneous success in the years following the bursting of the bubble. They then reacted to the over-correction, leading to a seemingly unexplainable factor failure in 2003. It is hard to find a similar damped oscillation periods in the data since 1971, perhaps because the dot.com distortion was uniquely powerful. Analogously, you only observe the dynamics of the earth's crust during earthquakes and they are rare.

Regression Studies

So, is the decline suggested by your eye and the simple trendlines the end of the story? Are quantitative factors losing their effectiveness? That may be the case, but there are some other possibilities. For example, perhaps there are systemic forces at work in the markets that have always affected the utility of quantitative factors, but that are themselves transitory. In that case, we may simply be seeing a temporary decline in effectiveness that will reverse itself when the market environment changes. To disentangle the various possible effects we turned to regression analysis to generate a fitted series that gets at the underlying trend, correcting for whatever else helps explain short-term fluctuations.

Seeking measures that may explain factor success rates, we find that contemporaneous market direction, market volatility (defined as the standard deviation of the 1,500 individual stock returns each month), and auto-correlation exhaust the list of generally significant independent variables. We included time-trend to test its significance in the presence of other explanatory factors.

Figure 8. Annual Momentum-Valuation Factor Success Rate



The resulting regression equation expressed factor success as a function of independent variables:

$$FS_t = f(k, FS_{t-1}, \Delta M_t, V_t, T)$$

Where:

FS_t = Factor Success for month t

k = constant

FS_{t-1} = Factor Success for month t-1

ΔM_t = Market percentage change for month t

V = market volatility for month t

T = Time Trend

Table 1 reports the regression results from 1971 through 2006 for all ten factors together, for the five valuation and five momentum factors combined, and for each individual factor. Although R-squares are modest, the regressions do explain some of the fluctuation in factor success rates and reveal the long-term trend. **Figures 9**, **10**, and **11** display the raw success rate data along with regression fits, labeled *corrected success,* for all factors and for the momentum and valuation factors treated separately.

Efforts to improve success rate regression fit by introducing variables such as interest rates, yield curve, S&P 500 earnings yield, unemployment, GNP, growth, or calendar effects were failures. Both lagged and contemporaneous data failed to improve fit. Various measures of cross lags in a vector-auto-regressive approach also fail. Complex ARIMA models capture the dynamics of the dot.com years, but are not apparent in the non-dot.com years. Likewise including future values of explanatory variables does not help regression fits, so we hold the success regression equation as a workman-like example of explaining success fluctuation.

The most powerful regression term is contemporaneous market direction. Its coefficient is negative, suggesting that factor success is greater in falling than rising markets. This relationship is strongest among valuation factors and evident in both the dot.com and non-dot.com years. We also observe that the lagged factor success term is positive and generally significant. This can be thought of as a correction for serial correlation in errors in the Box-Jenkins sense. For momentum factors, regressions fit over the entire database and in just the dot.com years reveal that market dependence generally drops from significance in the dot.com period.

Considering time trend, alternative formulations of trend specifying an asymmetric approach to a steady success rate or specifying a simple dummy variable for the dot.com era result in similar fits, but nothing attractively better than a linear trend, suggesting that linear time trend is the simplest explanation. After accounting for other explanatory factors, the time trend is generally of borderline statistical significance. If we limit the universe to just the S&P 500 stocks the time trend is insignificantly different from zero—in other words, there is no time trend apparent in the bigger cap stocks.

One interesting time trend finding provides further econometric support for the special status of the dot.com era and its aftermath. While the linear time trends exhibit borderline significant negative t-statistics for the entire time period from 1971 through 2006, they switch to zero t-statistics for regressions from 1996 through 2006. In short, the factor success trend data is consistent with either a steady down-trend in success rate, only visible over decades, or with a one-time drop in success during the dot.com era and subsequent (partial) recovery. If a steady-state down-trend is the true characterization, sooner or later the performance of optimized multifactor models must erode. If the apparent decline is only an artifact of the dot.com distortion, there is no reason to think that quantitative investing is coming to an end.

The fit series for all factors (**Figure 9**) suggests a slow decrease in corrected success rate toward a rolling twelve-month average level of around 55%. Comparing the separate momentum and valuation series, however, suggests that just one style may be responsible for much of this deterioration. The momentum factors (**Figure 10**) start out with a high corrected success rate, but seem to

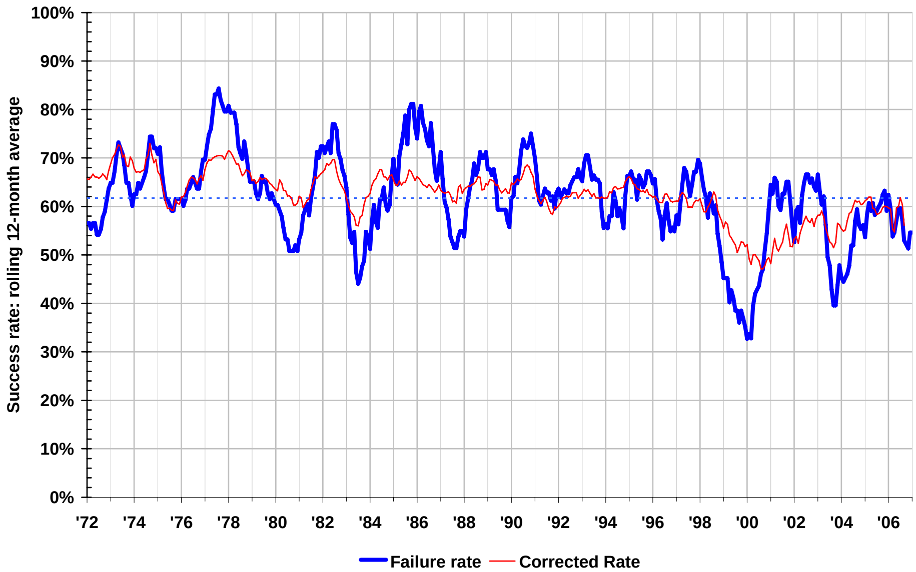
Table 1. Regression Results, Factor Success

FACTOR	K	ΔM_t	FS_{t-1}	V_t	T	R^2
All Factors	0.72 (15.4) *	-0.0130 (-6.8) *	0.120 (2.6) *	-0.0130 (-3.7) *	-0.0001 (-1.5)	0.19
Momentum Factors	0.83 (13.3) *	-0.0070 (-2.6) *	0.100 (2.1)	-0.0170 (-3.2) *	-0.0002 (-1.7)	0.09
PM	0.63 (4.3) *	-0.0380 (-4.5) *	0.023 (0.5)	0.0000 (0.0)	-0.0007 (-1.9)	0.06
EG	0.46 (2.8) *	-0.0050 (-0.6)	0.070 (1.3)	-0.0200 (-1.2)	-0.0030 (-0.8)	0.01
EC	0.96 (6.4) *	-0.0100 (-1.7)	0.130 (2.8) *	-0.0400 (-2.7) *	-0.0009 (-2.3) *	0.09
ER	1.90 (4.9) *	-0.0500 (-4.0) *	0.010 (0.2)	-0.0500 (-3.0) *	-0.0030 (-2.5) *	0.19
ES	1.30 (3.2) *	0.0060 (0.5)	0.030 (0.4)	-0.0700 (-3.7) *	-0.0010 (-0.9)	0.09
Valuation Factors	0.62 (10.4) *	-0.1800 (-6.2) *	0.150 (3.2) *	-0.0090 (-1.7)	-0.000 (-0.8)	0.13
EP	0.61 (3.9) *	-0.0400 (-4.4) *	0.140 (3.0) *	-0.0300 (-2.2)	-0.0002 (-0.4)	0.09
FEP	0.67 (1.6)	-0.0500 (-3.1) *	0.090 (1.2)	-0.0300 (-1.4)	-0.0006 (-0.5)	0.08
CF	0.59 (3.7) *	0.0012 (0.1)	0.140 (3.1) *	-0.0450 (-2.7) *	0.0003 (0.7)	0.05
BV	0.06 (0.3)	-0.0100 (-1.1)	0.160 (3.2) *	0.0017 (0.1)	0.0000 (0.0)	0.03
DY	0.20 (1.4)	-0.1000 (-12.7) *	0.110 (2.6) *	-0.0020 (-0.1)	-0.0004 (-1.0)	0.30

Note: Based on monthly returns in *the Columbine 1500 Universe,* 1971 through 2006. *T*-statistics in parentheses. Asterisks indicate *t*-statistics significant at 99%.

decline steadily from year to year, and drop off sharply in the wake of the dot.com bubble. In contrast, the valuation factor series (**Figure 11**) shows little change over time. The valuation factors have a lower corrected success rate overall, but exhibit little variation in that rate from year to year.

Figure 9. Overall Factor Success Rate with Corrected Rate



Implications for Performance Erosion

Will the observed factor success declines result in zero alphas from multifactor models?

We tested this by comparing out-of-sample model performance with factor success monthly and noting the regression intercept. We find that zero alpha occurs generally when factors approach a 50% success rate. Currently the rate is about 60% (rolling 12-months) for all factors, 55% for valuation, and 65% for momentum, down from highs of 70% or better in the 1970s. Considering trends apparent in **Figures 9**, **10**, and **11**, valuation appears stable at 55%, momentum may in the future decrease to the lower valuation success rate, but it has a way to go to get to zero alpha levels. We project future 1st/10th spread of all models of about 1% at one month holding compared to the average over the past thirty-five years of 1.9%. On an annualized basis, this is a 12% top-bottom decile spread instead of the 23% top-bottom spread seen in the 1970s and 1980s.

CONCLUSIONS

- Looking at success time trends using regression models, all ten factors, and valuation and momentum factors exhibit negative time trend coefficients, 90% significant for all factors, 95% for momentum, but only 77% for valuation. These down trends are evident in the success rate charts of the fit success regression models. Lower transaction costs and increased data availability over thirty-five years likely account for some of the decreased success.

- Valuation factors, in wide use for decades, exhibit slowly declining success rates and perhaps are at equilibrium now. What remains is a fairly stable return spread and success on average, but with risk of loss. Periodic failure is a risk inhibiting full exploitation, but perhaps guaranteeing a permanent, albeit volatile alpha.

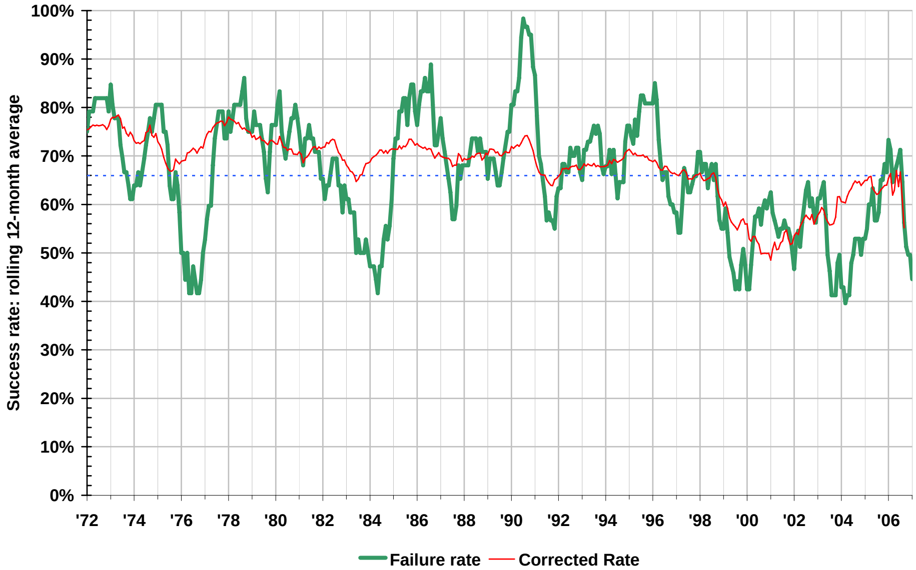
- Momentum factors, less widely used, started in the 1970s and 1980s with excellent success rates and have declined as estimate revision and price momentum gained increasing acceptance during the 1990s. The drop in momentum's success rate was most pronounced during the dot.com years. Nonetheless, momentum's success rate is still generally higher than valuation, perhaps because it is still less widely accepted.

- Considering all ten factors in S & P 500 stocks instead of the 1500, we find similar sensitivity to the market and to volatility and auto correlation, but an insignificant time trend. This fact suggests that there was a theoretical, but unrealizable small cap potential in the past when transactions cost were higher than they are now.

- There is stable significant negative market direction dependence suggested for factor success rate in valuation factors, and a weaker statistically less significant dependence for momentum. Greater factor success and better spread and 1st decile performance in down markets may reflect a flight to quality (value) in bear markets. In contrast in bull markets the idea that any stock will do is consistent with lower 1st/10th decile spreads in rising markets for both styles.

- The negative market correlation seen in success and return regressions suggest that multifactor quant models are more than alpha producers. They are also absolute return volatility reducers, providing some

Figure 10. Momentum Factor Success Rate with Corrected Rate



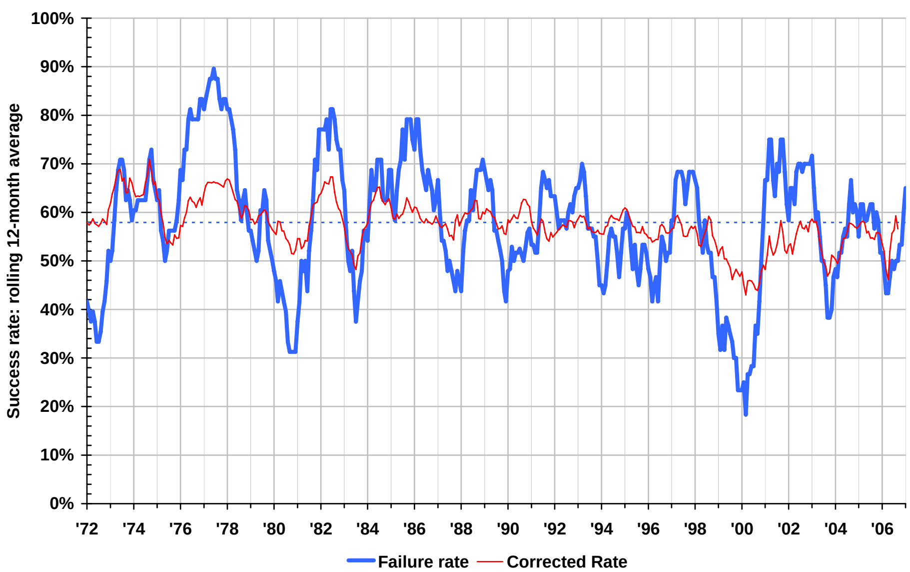
long alpha in rising markets, but higher long alphas in down markets, cushioning declines. This has the beneficial effect of reducing volatility of absolute return. In effect, quant models are effectively lower beta in falling markets than in rising. Not surprisingly dividend yield is uniquely powerful for this role.

- Dot.com era distortions are the likely cause of simultaneous recent extreme failure rates for factors on the way up and extreme success on the way down. Eventual return to normal market conditions may see a return to normal negatively correlated success rate fluctuation.

- While real factor success rates may be declining, they have a considerable way to drop before producing an zero expected alpha from multifactor models constructed from these factors. For the foreseeable future the most likely outcome is reduced alpha (as compared with past decades), but not an end to the utility of quantitative investment tools.

- With traditional factors in wide use, exploration of factor improvements: *e.g.*, non-linearity of interactions or new approaches to exploiting existing factor anomalies may offer improved multifactor model success until these new tools also become more widely used

Figure 11. Valuation Factor Success Rate with Corrected Rate



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Appendix I. Success Rate by Factor and Calendar Month: 1971-2006

Columbine 1500 Universe

Factor	Overall	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
All Factors	61.2%	54.3%	60.1%	65.7%	59.7%	53.8%	65.7%	69.3%	57.8%	67.7%	61.4%	55.1%	63.0%
Momentum Factors	65.4%	48.1%	64.8%	67.6%	62.0%	54.2%	73.2%	71.8%	63.4%	78.2%	71.1%	58.5%	67.6%
EPS Change	70.1%	55.6%	69.4%	66.7%	69.4%	52.8%	75.0%	77.8%	75.0%	75.0%	83.3%	75.0%	66.7%
EPS Growth	59.7%	27.8%	58.3%	58.3%	50.0%	50.0%	63.9%	69.4%	55.6%	80.6%	69.4%	61.1%	72.2%
Price Momentum	68.9%	NA	75.0%	75.0%	72.2%	50.0%	77.8%	69.4%	58.3%	86.1%	72.2%	52.8%	69.4%
EPS Surprise*	60.8%	58.8%	58.8%	58.8%	58.8%	58.8%	58.8%	58.8%	58.8%	58.8%	58.8%	58.8%	58.8%
Estimate Revision*	65.2%	64.7%	64.7%	64.7%	64.7%	64.7%	64.7%	64.7%	64.7%	64.7%	64.7%	64.7%	64.7%
Valuation Factors	57.6%	58.4%	55.9%	64.0%	57.8%	53.4%	59.0%	67.1%	52.8%	58.4%	52.8%	52.2%	59.0%
Book Value	57.4%	75.0%	58.3%	72.2%	61.1%	55.6%	50.0%	61.1%	50.0%	52.8%	44.4%	55.6%	52.8%
Cash Flow	61.3%	61.1%	61.1%	72.2%	66.7%	52.8%	58.3%	72.2%	58.3%	55.6%	50.0%	55.6%	72.2%
Dividend Yield	49.5%	38.9%	50.0%	41.7%	38.9%	52.8%	61.1%	66.7%	47.2%	55.6%	55.6%	38.9%	47.2%
Reported EPS Yield	61.6%	61.1%	55.6%	66.7%	61.1%	55.6%	61.1%	66.7%	61.1%	69.4%	63.9%	52.8%	63.9%
Estimated EPS Yield*	58.3%	52.9%	52.9%	70.6%	64.7%	47.1%	70.6%	70.6%	41.2%	58.8%	47.1%	64.7%	58.8%

** 1990 to 2006*

S&P 500 Index Universe

Factor	Overall	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
All Factors	56.7%	47.6%	55.4%	61.7%	57.1%	54.5%	56.8%	59.1%	54.8%	64.4%	57.8%	48.5%	61.4%
Momentum Factors	59.1%	47.2%	56.3%	57.0%	58.5%	56.3%	65.5%	62.0%	54.9%	73.2%	64.1%	47.2%	64.1%
EPS Change	62.0%	58.3%	63.9%	63.9%	52.8%	58.3%	69.4%	55.6%	61.1%	77.8%	63.9%	58.3%	61.1%
EPS Growth	53.9%	27.8%	47.2%	52.8%	61.1%	50.0%	55.6%	50.0%	44.4%	72.2%	66.7%	52.8%	66.7%
Price Momentum	61.6%	NA	52.8%	55.6%	66.7%	52.8%	72.2%	72.2%	50.0%	77.8%	72.2%	44.4%	61.1%
EPS Surprise*	55.4%	52.9%	52.9%	52.9%	52.9%	52.9%	52.9%	52.9%	52.9%	52.9%	52.9%	52.9%	52.9%
Estimate Revision*	62.7%	58.8%	58.8%	58.8%	58.8%	58.8%	58.8%	58.8%	58.8%	58.8%	58.8%	58.8%	58.8%
Valuation Factors	54.6%	47.8%	54.7%	65.8%	55.9%	52.8%	49.1%	56.5%	54.7%	56.5%	52.2%	49.7%	59.0%
Book Value	53.0%	61.1%	58.3%	72.2%	58.3%	50.0%	33.3%	50.0%	50.0%	50.0%	44.4%	52.8%	55.6%
Cash Flow	53.7%	50.0%	55.6%	61.1%	63.9%	52.8%	50.0%	52.8%	55.6%	50.0%	47.2%	44.4%	61.1%
Dividend Yield	52.8%	33.3%	44.4%	55.6%	50.0%	55.6%	61.1%	61.1%	50.0%	63.9%	61.1%	41.7%	55.6%
Reported EPS Yield	59.3%	47.2%	58.3%	69.4%	50.0%	52.8%	52.8%	63.9%	66.7%	69.4%	58.3%	61.1%	61.1%
Estimated EPS Yield*	53.4%	47.1%	58.8%	76.5%	58.8%	52.9%	47.1%	52.9%	47.1%	41.2%	47.1%	47.1%	64.7%

** 1990 to 2006*

Appendix II. Extreme Low Factor Successes: History

Months in which 40% or less of all individual factors worked (positive top-bottom spread)

Universe: Columbine 1500
Period: 1971 through 2006

Year	Month	Success Rate
1971	Dec	29%
1973	May	29%
1978	Oct	29%
1980	Nov	29%
1981	May	29%
1982	Aug	29%
1982	Oct	14%
1983	Jan	0%
1983	May	0%
1983	Nov	29%
1983	Dec	29%
1984	Mar	29%
1984	Aug	14%
1985	Jan	17%
1985	Jul	29%
1987	Jan	17%
1987	Feb	29%
1987	May	29%
1988	Dec	29%
1989	Apr	29%
1989	May	0%
1990	Nov	40%
1991	Feb	30%
1992	Jan	22%
1992	Feb	40%
1993	Apr	40%
1993	May	40%
1993	Oct	0%
1993	Nov	20%
1994	May	20%
1994	Sep	40%
1995	Jun	40%
1996	Feb	20%
1996	Mar	40%
1996	Apr	30%
1996	May	30%
1996	Aug	20%
1996	Sep	40%
1997	May	20%
1998	Jan	22%
1998	Feb	40%
1998	Apr	20%
1998	Jul	40%

Month	Count
Jan	9
Feb	8
Mar	4
Apr	7
May	11
Jun	3
Jul	4
Aug	6
Sep	4
Oct	6
Nov	9
Dec	6
All	**77**

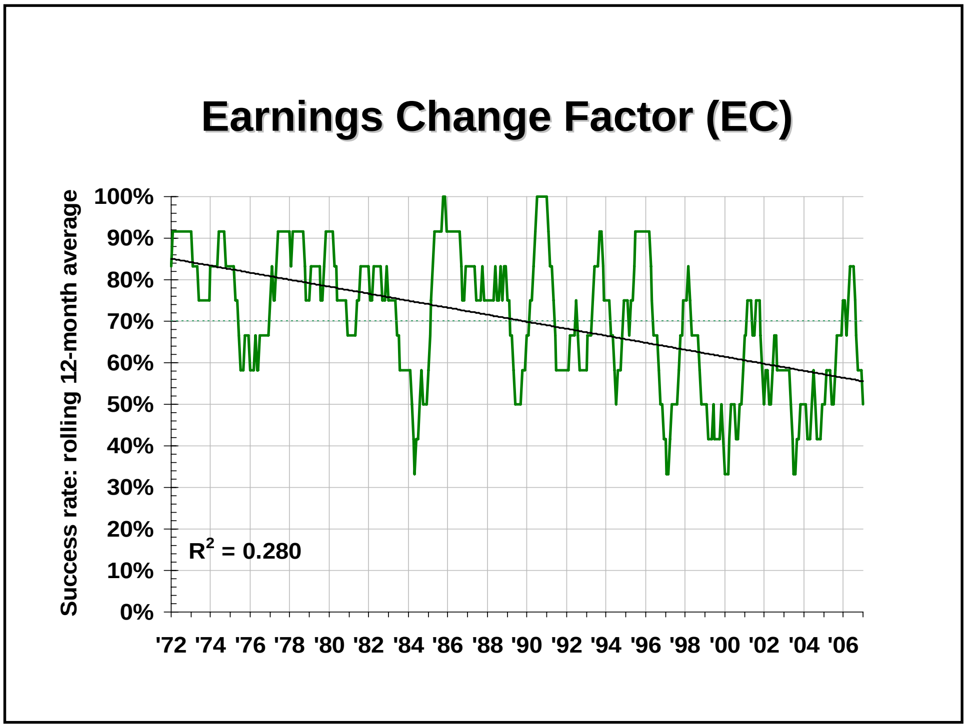
Year	Count
1971	1
1972	0
1973	1
1974	0
1975	0
1976	0
1977	0
1978	1
1979	0
1980	1
1981	1
1982	2
1983	4
1984	2
1985	2
1986	0
1987	3
1988	1
1989	2
1990	1
1991	1
1992	2
1993	4
1994	2
1995	1
1996	6
1997	1
1998	6
1999	10
2000	3
2001	5
2002	3
2003	4
2004	3
2005	2
2006	2
All	**77**

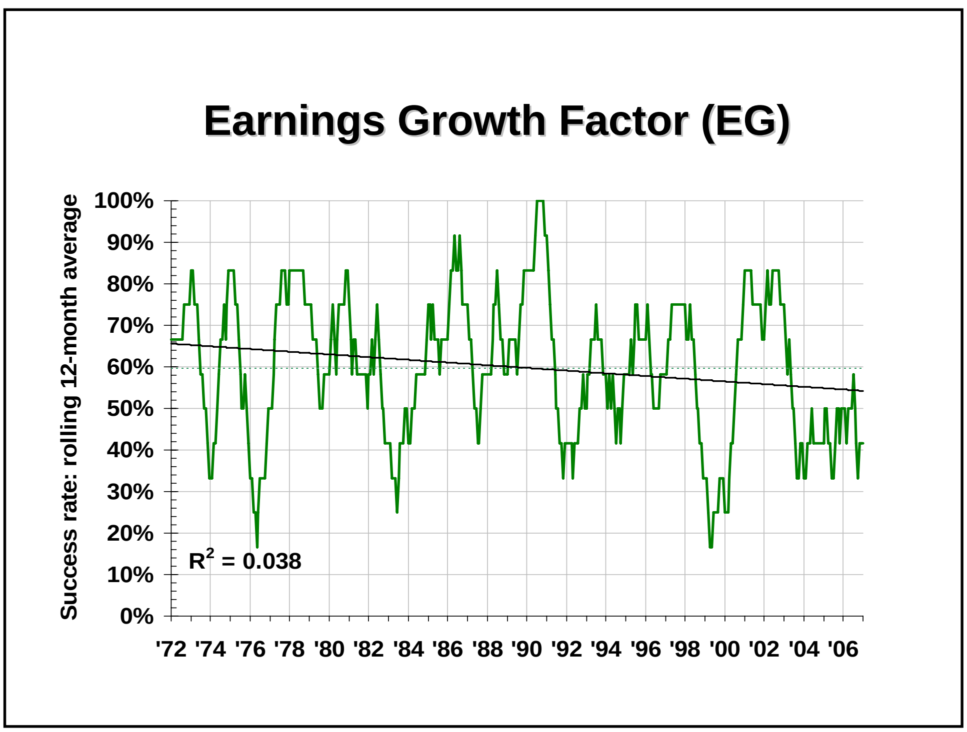
Appendix II. Extreme Low Factor Successes: History

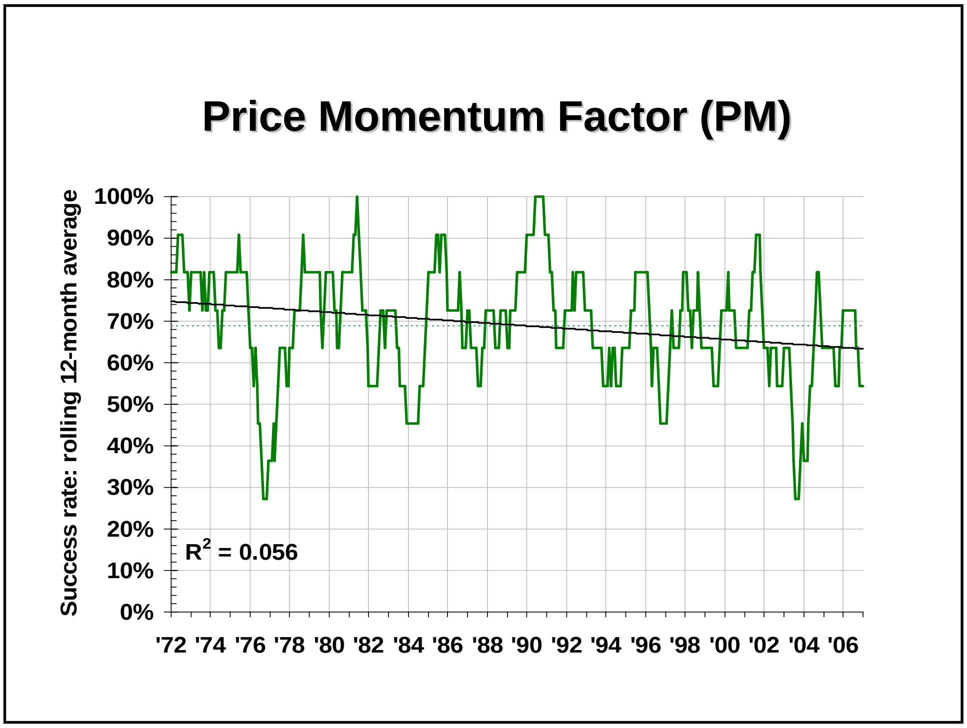
Months in which 40% or less of all individual factors worked (positive top-bottom spread)

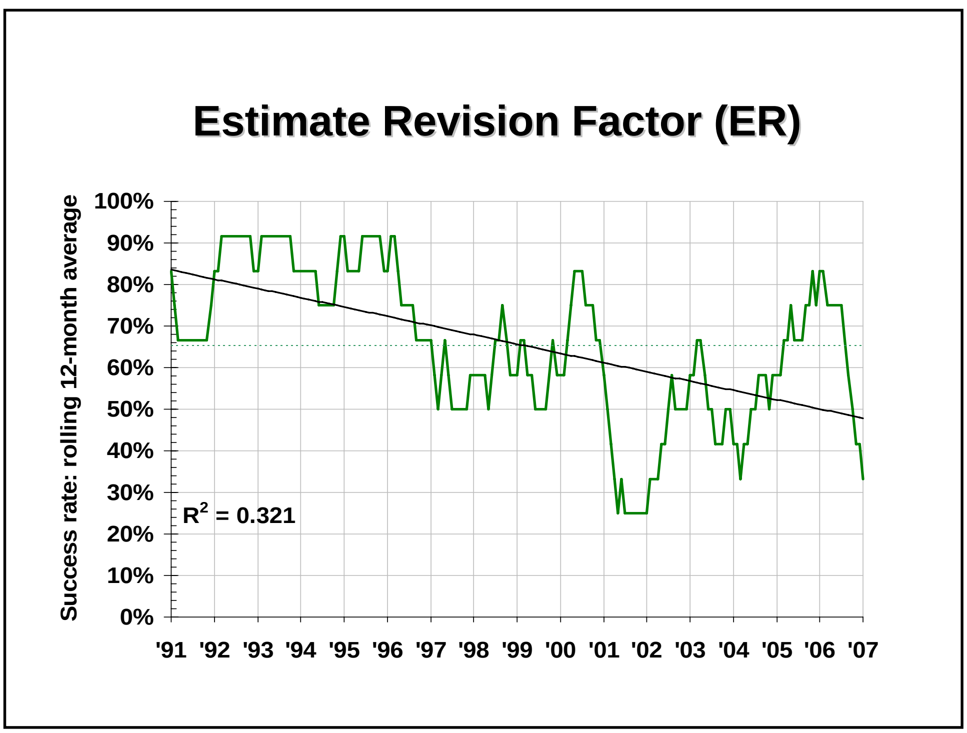
Universe: Columbine 1500
Period: 1971 through 2006

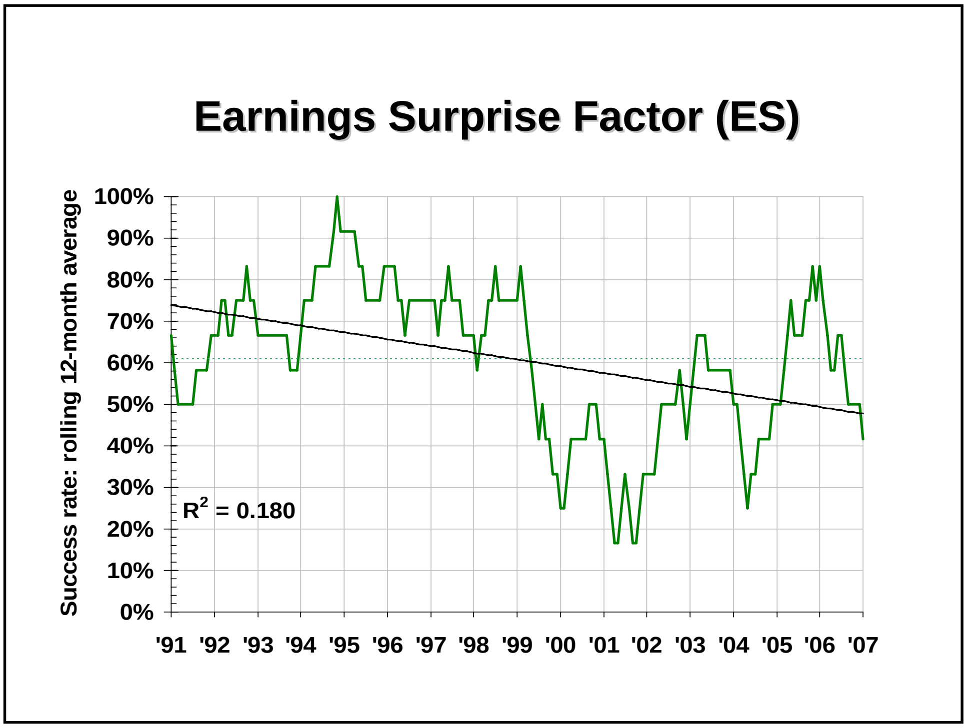
Year	Month	Success Rate
1998	Sep	0%
1998	Nov	40%
1999	Jan	22%
1999	Feb	40%
1999	Mar	10%
1999	Jun	20%
1999	Jul	40%
1999	Aug	40%
1999	Sep	30%
1999	Oct	40%
1999	Nov	20%
1999	Dec	20%
2000	Jan	33%
2000	Feb	30%
2000	Jun	30%
2001	Jan	11%
2001	Apr	20%
2001	Oct	30%
2001	Nov	20%
2001	Dec	40%
2002	Mar	40%
2002	Oct	10%
2002	Nov	10%
2003	Apr	20%
2003	May	10%
2003	Jul	10%
2003	Aug	20%
2004	Jan	33%
2004	Apr	40%
2004	Dec	20%
2005	May	30%
2005	Nov	20%
2006	Feb	20%
2006	Aug	10%

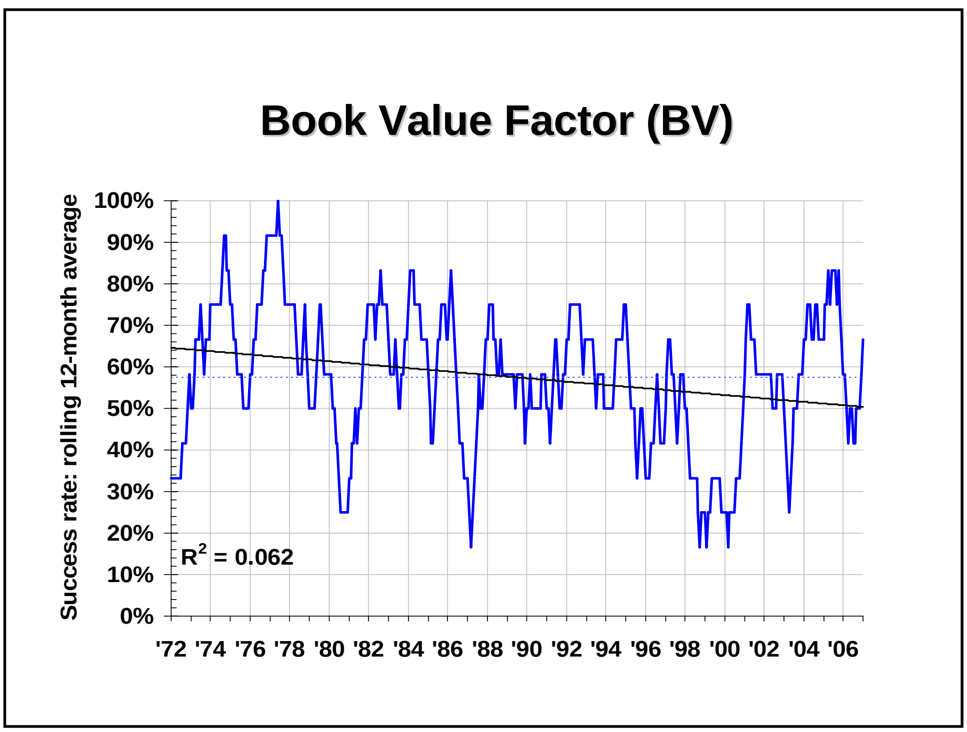

Earnings Change Factor (EC)
Success rate: rolling 12-month average
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
R2 = 0.280
'72 '74 '76 '78 '80 '82 '84 '86 '88 '90 '92 '94 '96 '98 '00 '02 '04 '06

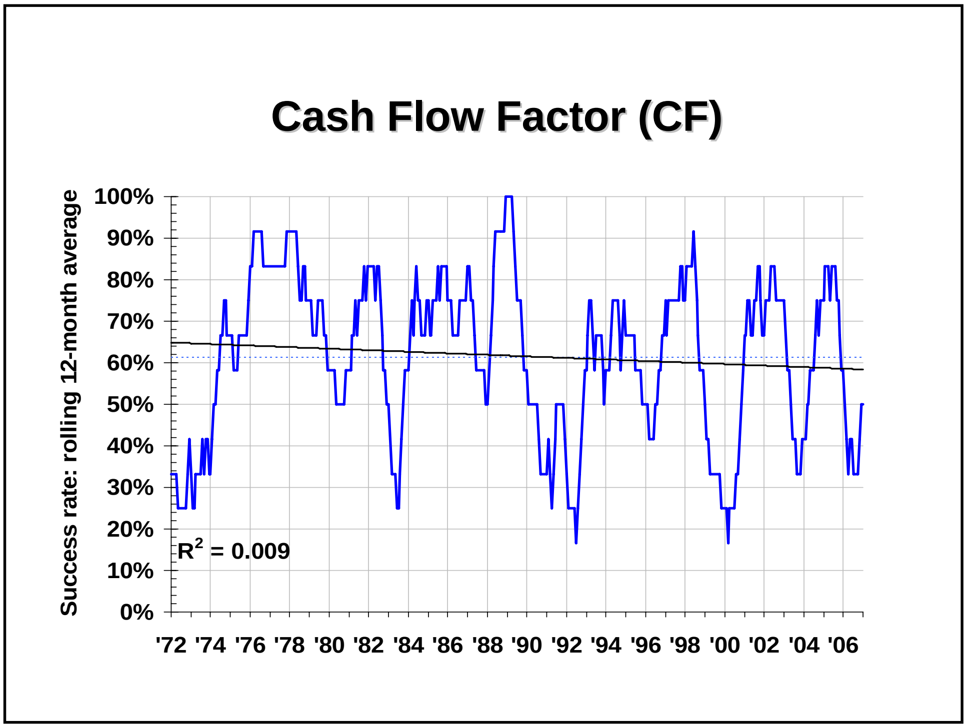

Earnings Growth Factor (EG)
Success rate: rolling 12-month average
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
R2 = 0.038
'72 '74 '76 '78 '80 '82 '84 '86 '88 '90 '92 '94 '96 '98 '00 '02 '04 '06

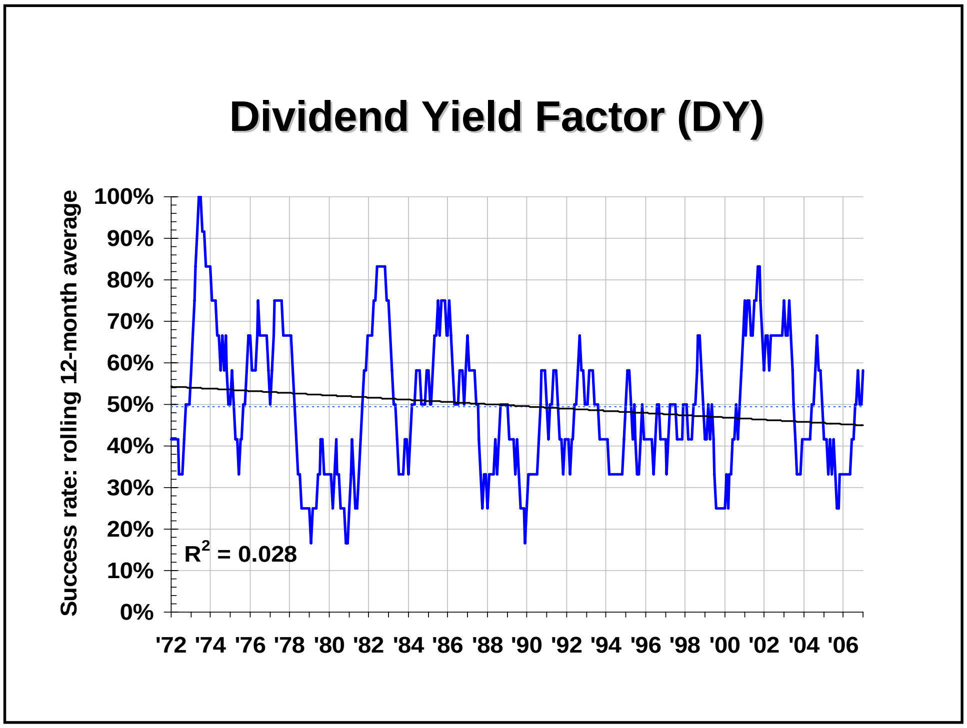

Price Momentum Factor (PM)
Success rate: rolling 12-month average
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
R^2 = 0.056
'72 '74 '76 '78 '80 '82 '84 '86 '88 '90 '92 '94 '96 '98 '00 '02 '04 '06

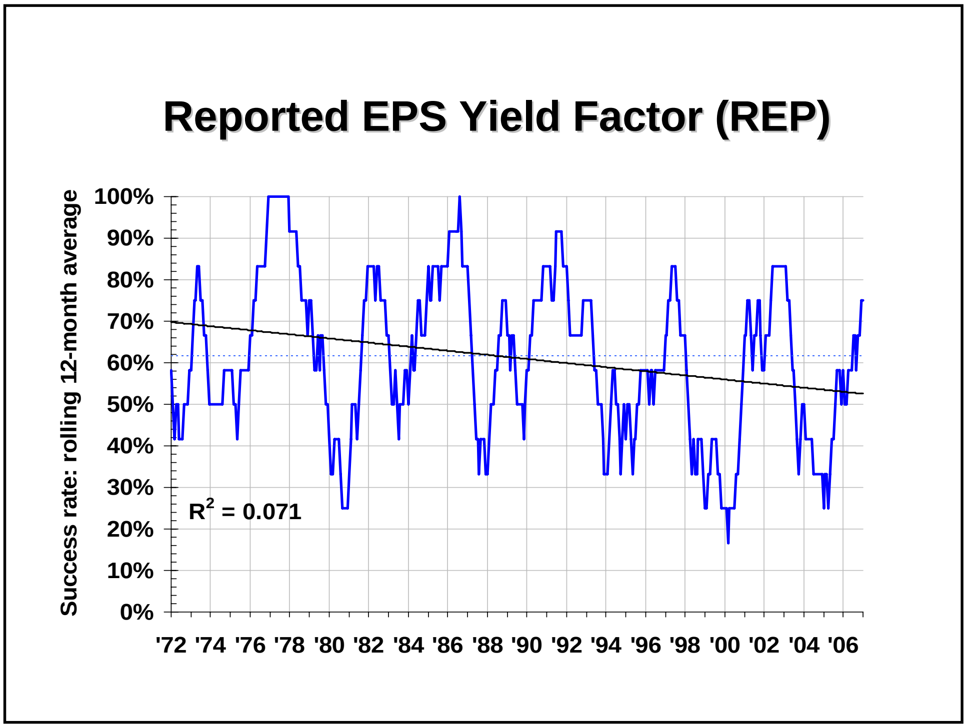

Estimate Revision Factor (ER)
Success rate: rolling 12-month average
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
R^2 = 0.321
'91 '92 '93 '94 '95 '96 '97 '98 '99 '00 '01 '02 '03 '04 '05 '06 '07

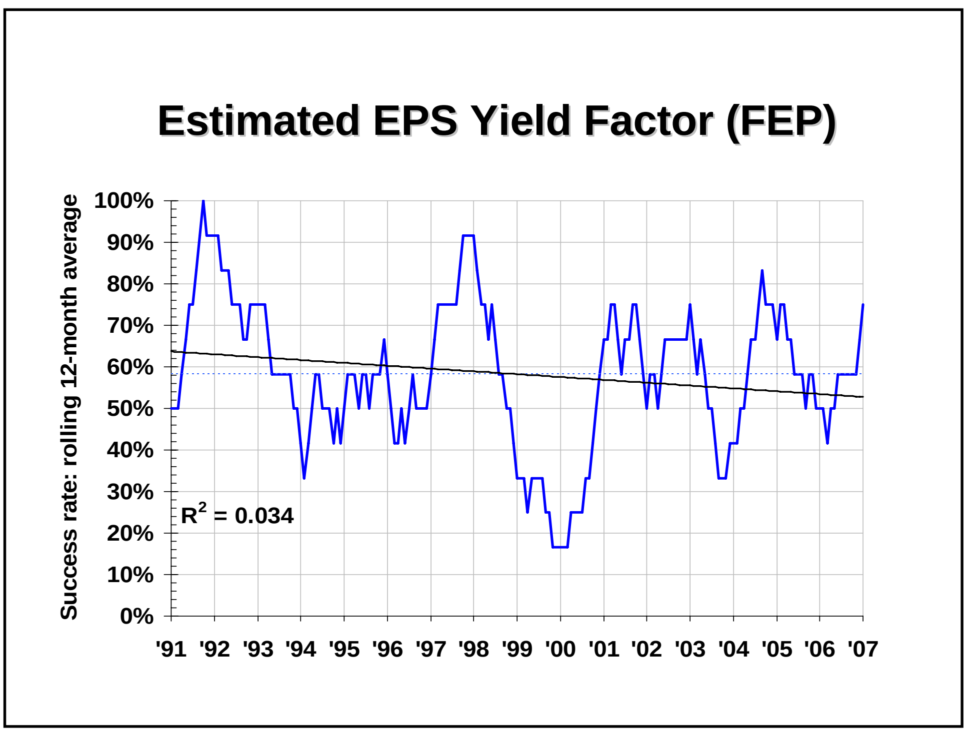

Earnings Surprise Factor (ES)
Success rate: rolling 12-month average
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
R^2 = 0.180
'91 '92 '93 '94 '95 '96 '97 '98 '99 '00 '01 '02 '03 '04 '05 '06 '07


Book Value Factor (BV)
Success rate: rolling 12-month average
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
R^2 = 0.062
'72 '74 '76 '78 '80 '82 '84 '86 '88 '90 '92 '94 '96 '98 '00 '02 '04 '06


Cash Flow Factor (CF)
Success rate: rolling 12-month average
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
R^2 = 0.009
'72 '74 '76 '78 '80 '82 '84 '86 '88 '90 '92 '94 '96 '98 '00 '02 '04 '06


Dividend Yield Factor (DY)
Success rate: rolling 12-month average
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
R^2 = 0.028
'72 '74 '76 '78 '80 '82 '84 '86 '88 '90 '92 '94 '96 '98 '00 '02 '04 '06


Reported EPS Yield Factor (REP)
Success rate: rolling 12-month average
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
R^2 = 0.071
'72 '74 '76 '78 '80 '82 '84 '86 '88 '90 '92 '94 '96 '98 '00 '02 '04 '06


Estimated EPS Yield Factor (FEP)
Success rate: rolling 12-month average
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
R^2 = 0.034
'91 '92 '93 '94 '95 '96 '97 '98 '99 '00 '01 '02 '03 '04 '05 '06 '07