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A Case Study for Using Value and Momentum at the Asset Class Level

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This article explores a globally diversified asset allocation strategy driven by value and momentum factors. The authors find that adjusting for value and momentum yields higher and better quality returns that are statistically and economically significant. This research differs from the existing literature in that it examines the value and momentum effects at the asset class level and uses a long-only approach. The research employs simple nonoptimized metrics for value and momentum, which reduce the chances that the authors' results are attributable to data mining. The authors find that dynamic asset allocation based on simple valuation and momentum metrics would have added roughly 266 basis points of excess annualized return over the sample period 1975–2013.

A Case Study for Using Value and Momentum at the Asset Class Level

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The consensus advice proffered to nonprofessional investors is to buy a diversified portfolio of risky assets and hold for the long term, while parking some percentage of the portfolio in low-risk assets that are expected to outperform during market downturns. Explicit in this counsel is the view that the nonprofessional investor should not expect to beat the market, either by picking individual investments that will outperform or by identifying investment managers who can generate above-market returns.

However, the shortcomings of passive investing have been widely documented. Critics question the wisdom of blindly holding a portfolio with weights determined by market values in the face of recurring bubbles and panics. They point out that in 1989, when the Japanese stock market was trading at close to 100 times earnings, a passive index portfolio of global equities would have had roughly 40% allocated to Japanese equities.

A large body of research has been put forth attempting to reconcile these two seemingly incompatible views of the market: on one hand, markets are very efficient and thus difficult to beat; but on the other hand, they tend to exhibit periods in which valuations move far away from intrinsic values. Two important findings in the literature are that value and momentum are two persistent and often opposing characteristics of asset price dynamics.

As shown by Campbell and Shiller [1988], Fama and French [1989], Ferson and Harvey [1991], and Cochrane [2008], asset risk premia are not constant through time. Periods of heightened risk aversion, such as economic downturns, are associated with higher required return premia, resulting in lower asset valuations. This literature finds that markets are efficiently pricing risk, but that both risk and the price of risk are not static.

In addition, many studies find momentum across time and assets. Jegadeesh and Titman [1993] and Asness [1995] examined the impact of momentum cross-sectionally in equity markets. Pirrong [2005] used a cross-market perspective and found significant returns for momentum strategies across futures markets. Moskowitz and Grinblatt [1999] found momentum in sectors and industries. Moskowitz, Ooi, and Pedersen [2012] documented time-series momentum across 58 liquid instruments showing that momentum is longitudinal as well as cross-sectional. Few risk premium-based explanations have been put forth for the momentum effect, but many plausible behavioral arguments—such as anchoring, the disposition effect, herding, and confirmation bias—have been suggested. Some elements of market structure, such as the effect of government intervention and VaR-based risk management regimes, may also play a role. We favor the explanations that are based on feedback loops—what George Soros explains as reflexivity.[1]

Only recently have value and momentum been studied in combination and across markets. Recent research finds that value and momentum effects offer higher returns and lower risk when used in combination rather than independently, primarily because value and momentum tend to operate over different time horizons. The negative correlation arises from value investing's reliance on reversion to fair value (i.e., negative autocorrelation), while momentum investing is predicated on divergence from the mean (i.e., positive autocorrelation). Often, momentum acts as a check on value, discouraging an investor from buying before a bottom or selling before a peak. The attractiveness of the combined value and momentum approach was documented over a broad range of assets by Asness, Moskowitz, and Pedersen [2013]. We too find that value and momentum are negatively correlated and are thus best implemented in an integrated framework.

Extending much of the recent literature on asset-pricing dynamics, we examine whether simple, non-optimized value and momentum factors would work on average in a long sample that includes multiple business cycles, monetary regimes, and economic and financial crises. Using data from 1975 to 2013, we find that 1) valuation-based scaling of asset allocations produces a return that exceeds a static-weight portfolio by 86 basis points (bps) per annum, 2) momentum-based scaling of asset allocations produces a return that exceeds a static-weight portfolio by 155 bps per annum, and 3) the combination of these two portfolio adjustments produces returns that exceeds the static-weight portfolio by 266 bps per annum.[2] The dynamically scaled portfolios also produce higher Sharpe ratios. The portfolios do not employ leverage (explicitly or implicitly through the use of futures or derivatives), do not take short positions, and do not allow for significant concentration of risk in a small subset of the asset classes.

Our research adds to the existing literature by examining the widely documented value and momentum effects found within asset classes to uncover whether these effects are also present at the asset class level. Additionally, our research focuses on long-only portfolios rather than the more common approach of using long–short portfolios. The time period—back to 1975 for our most comprehensive study and to 1926 for two additional studies—is also novel in the literature concerning value and momentum effects at the asset class level. The research most similar to ours is Blitz and van Vliet [2008]; however, they examine different asset classes, scaling metrics, and time horizons. Others such as Wang and Kochard [2011] and Gnedenko and Yelnik [2014] use different methodologies to explore the impact of using an integrated value and momentum framework at the asset class level. Despite the varying approaches, most previous research shows that scaling asset exposures on value and momentum factors enhances returns and return quality.

This article is organized as follows. The next section describes our data and methodology. The subsequent section describes the performance of test portfolios and various robustness tests. We conclude by offering some possible explanations for our results and suggesting various improvements and extensions.

DATA AND METHODOLOGY

Our research is primarily concerned with the period from 1975 to 2013. We also built portfolios with a more limited set of assets using a sample period from 1926 to 2013. The breadth and quality of data in the 1926–2013 sample is inferior to the 1975–2013 sample; however, it is novel to the value and momentum literature and includes a more diverse set of economic conditions. Therefore, we discuss the results from these longer-dated portfolios where appropriate and treat them as an imperfect, but worthwhile, out-of-sample test.

Exhibit 1 is an overview of the 12 asset classes that constitute the portfolios in our analyses. Equity data is sourced from MSCI and Robert Shiller; treasury data is from the Federal Reserve and Robert Shiller. Inflation survey data comes from the Federal Reserve and a proprietary data series provided by Antti Ilmanen. Commodities data is the Goldman Sachs Commodity Index (GSCI) taken from Bloomberg. Real Estate data comes from the FTSE NAREIT All REIT Index. More specific details on the data used can be found in the appendix.

The asset classes in this study are based on the following criteria:

- assets that carry risk that cannot be diversified away (i.e., systematic risk)
- assets available for investment through liquid, low-cost vehicles, such as index funds and ETFs with low management fees

EXHIBIT 1
Baseline Composition of Portfolios

Asset Class	Valuation Centering Level	Portfolio Weights: 1975–2013 Intnl Portfolio	Portfolio Weights: 1926–2013 Intnl Portfolio	Data Sources: Data 1975	Data Sources: Data 1926
U.S. Equities	6%	20.9%	35%	MSCI	SP
U.K. Equities	6%	4.0%	20%	MSCI	FTSE
Europe X U.K. Equities	6%	7.4%	0	MSCI	NA
Japan Equities	6%	7.7%	10%	MSCI	TOPIX
Pacific X Japan Equities	6%	1.6%	0	MSCI	NA
Canada Equities	6%	1.4%	0	MSCI	NA
EM Equities	6%	2.0%	0	MSCI	NA
U.S. REITS	6%	10%	0	NAREIT	NA
Commodities GSCI	1	10%	0	GSCI	NA
U.S. Nominal Treasuries	3%	10%	20%	Fed	Fed
U.S. Investment Grade Credit	1.5%	10%	0%	Moody's	Moody's
Cash (90 Day Treasuries)	NA	15%	15%	Fed	Fed

Note: For the 1975–2013 study, equity weights are averaged over the period.

- assets for which reasonably accurate historical data exist, including total returns (with dividends) and valuation metrics, such as earnings.

VALUE AND MOMENTUM METRICS

For each asset class, we determined a value signal and a momentum signal. For momentum, we used a 12-1 month lagged return series specification, which has evolved into an industry standard.[3] Lagging the returns helps account for liquidity issues, which are not pertinent to most of the asset classes in our research. Nonetheless, we used the lagged approach to maintain uniformity across asset classes and remain consistent with the literature.

Creating common value measures is less straightforward. We used a Shiller earnings yield (E/P) for equities in which earnings are the average of the past 10 years of inflation-adjusted corporate earnings on that index and price is the current stock market index level. For U.S. 10-year Treasury notes, we used the 10-year implied real rate, which is the difference between the current yield of the 10-year Treasury note and the next 10 years' forecasted inflation (via surveys). For corporate bonds, we used the credit spread relative to U.S. Treasuries plus the 10-year implied real rate of the 10-year U.S. Treasury as described above. We determined the credit spread as the yield difference between duration-matched indexes of corporate bonds and U.S. Treasuries. For commodities (GSCI Index), we used the ratio of the average inflation-adjusted price over the past 10 years to the current spot price. Our measure for real estate (REIT Index) is the dividend yield based on average inflation-adjusted dividends from the previous 10 years on the REIT Index.

In contrast to much of the existing literature that ranks assets based on valuation (or other factors) and then subsequently builds long–short portfolios from those rankings, we build long-only portfolios. This distinction is important because it forces us to choose "fair value" centering points for our valuation signal. Intuitively, these centering points should be thought of as asset valuations that provide fair compensation for bearing the risk associated with a specific asset class. At the end of each month in the sample, we derived a valuation signal for each asset class and if the signal was above (below) that centering point, signaling undervaluation (overvaluation), we increase (decrease) the allocation relative to its baseline weight in the subsequent month and vice versa.

There is no consensus—in the literature or by practitioners—on the ideal metric or level for measuring valuation in each asset class. In deriving our centering points, we attempted to balance common sense practitioner metrics with the findings in the asset-pricing literature. In an effort to reduce bias, we tried to select these centering points ex-ante and did not change or optimize them at any point in the research. An overview of the centering points can be found in Exhibit 1, and the interested reader can find more detailed descriptions and rationales in the appendix. We perturb all of the centering point levels and test alternative valuation metrics without experiencing a material impact on the results. We discuss these results in the *Caveats* section.

PORTFOLIO CONSTRUCTION

Using the measures above, we constructed four portfolios at the end of each month: baseline (no adjustment), value, momentum, and value + momentum. Rather than give equal weighting to each asset class, we approximately followed a 65/35 (equities/bonds) portfolio construction method.[4] We employed this approach because giving equal weight to each asset class regardless of its market capitalization is not a realistic backtest for most investors. The crux of our research is testing the impact of valuation and momentum scaling against non-scaled weights, so the initial weightings are not integral to the results. Return decomposition by asset class confirms this finding and is discussed below. We also built a portfolio that gave equal weight to each asset class (20% equities, 20% real estate, 20% commodities, 20% bonds, and 20% T-bills) and report the performance in Exhibit 2. The return enhancement from value- and momentum-based dynamic asset allocation is similar to the enhancement in the case of the 65/35 portfolio. It gives us comfort that this substantially different baseline allocation does not materially change the improvement provided by applying value and momentum at the asset class level.

Exhibit 2

Portfolio Performance Statistics (real annual returns, except for worst 5-year, which are total returns)

		Results of Studies			
		Baseline	**Value**	**Momentum**	**Val + Mom**
Study 1	Mean Return	5.77%	6.63%	7.32%	8.43%
Intnl (1975)	Stdev	9.05%	9.09%	9.09%	9.17%
	Sharpe	.50	.59	.67	.78
	t-stat	NA	2.2	3.2	4.6
	Worst 1-Yr	–35.4%	–34.0%	–23.1%	–20.2%
	Worst 5-Yr	–18.6%	–21.4%	–5.6%	2.5%
	Worst 1-Yr vs Baseline	NA	–5.7%	–16.7%	–7.8%
	Worst 5-Yr vs Baseline	NA	–16.5%	–8.5%	–1.4%
Study 2	Mean Return	5.28%	6.38%	6.87%	7.94%
Equal Weights	Stdev	7.89%	8.62%	8.51%	8.87%
	Sharpe	.51	.60	.66	.76
	t-stat	NA	3.2	3.3	5.3
	Worst 1-Yr	–35.1%	–34.2%	–24.4%	–23.2%
	Worst 5-Yr	–18.6%	–20.7%	–0.7%	3.7%
	Worst 1-Yr vs Baseline	NA	–5.6%	–13.9%	–4.7%
	Worst 5-Yr vs Baseline	NA	–9.9%	–2.8%	4.3%

Note: The return figures are annual, inflation-adjusted geometric returns.

For U.S. Treasuries, U.S. corporates, the GSCI, and REITS, the baseline weighting was held constant. For equity markets, we used market capitalization weights as published by MSCI on an annual basis. To improve the likelihood that our results are robust to cyclical economic and financial conditions, we kept the number of parameters to a minimum and held the non-optimized parameters constant through time.

1. For the Baseline (non-adjusted) portfolio, we rebalanced back to the initial weights at the end of each month.
2. Using the valuation measures, we scaled the exposure to each asset in the portfolio as follows:

$$\text{Weight}_{i,t}^{VALUE} =$$
$$BW_i * \left(1 + \max\left[-\frac{1}{2}, \min\left[\log\left(\frac{v_{i,t}}{c_i}\right), \frac{1}{2}\right]\right]\right) \quad (1)$$

c_i is the centering point for the ith asset, $v_{i,t}$ is the value signal (e.g., cyclically adjusted earnings yield) for the ith asset, and BW is the Baseline weight of the asset as found in Exhibit 1.

3. We increased an asset class's weight by 1/2 if the momentum signal was positive and decreased the weight by 1/2 if the momentum signal was negative.[5]

$$\text{Weight}_{i,t}^{MOMENTUM} = \begin{cases} BW_i \times \frac{3}{2} & \text{if Signal} > 0 \\ BW_i \times \frac{1}{2} & \text{if Signal} < 0 \end{cases} \quad (2)$$

4. Finally, we applied a no-leverage constraint if the desired portfolio had an aggregate weighting that exceeded 1 (excluding cash, which we treated as a residual when the weights added to less than 1). We accomplished this by scaling the individual asset weights down by the sum of the desired weights:

$$r_t^S = \frac{\sum_i^N w_{it}^S r_{it}}{\max\left(\sum_i^N w_{it}^S, 1\right)} \quad (3)$$

where $S \in$ {value, momentum, value + momentum}.

This four-step process produces the historical return results presented in this article. We repeated these steps on a monthly basis for each portfolio. For the **Baseline** (B) portfolio we stopped at step 1, rebalancing back to the initial fixed weights at the end of each month. For the **Baseline + Value** (B+V) strategy, we left out step 3. For the **Baseline + Momentum** ($B + M$) strategy, we omitted step 2. The focus of this article is the **Baseline + Value + Momentum** ($B + V + M$) strategy in which all four steps are performed at the end of each month.

RESULTS

Returns

We find a number of interesting results related to the interaction of value and momentum factors in our portfolio. Scaling based on value or momentum alone, or in combination, offers higher returns and Sharpe ratios than the static-weight Baseline portfolio. This finding is consistent across time horizons and produces significant t-statistics. Summary statistics are presented in Exhibit 2.

Value scaling adds 86 bps per annum to long-term performance, whereas momentum scaling adds 155 bps per annum. The return enhancements from incorporating our momentum factor are surprisingly large, and in general are more attractive than those arising from valuation-based scaling. Changing asset allocations based on value and momentum adds 266 bps of annual return, offers a Sharpe ratio that is more than 50% higher than the baseline, and reduces risk as measured by the maximum one- and five-year drawdowns. The fact that these results are achieved over nearly 40 years in a variety of market conditions gives us reason to believe that value and momentum are persistent features of asset-pricing dynamics. This excess annualized return is achieved without the use of shorting, leverage, individual security selection, or significant concentration.

The return contribution in the $B + V + M$ portfolio from each scaling factor (e.g., value, momentum, and the combination of value and momentum) can be found in Exhibit 3. The returns are essentially all positive. It is interesting to note that there was no asset class for which value and momentum scaling together diminished returns.

The results presented in Exhibit 2 are materially impacted by the portfolio's no-leverage constraint. To illustrate this, we constructed portfolios consisting of 50% cash and 50% of a specific asset and present the results in Exhibit 4. A test portfolio consisting of 50% equities and 50% cash provides 43bps of extra return from value scaling, 150bps from momentum scaling, and 194bps from the combination of value and momentum. However, in the context of the larger portfolio, value and momentum scaling of equities adds 28bps and 68bps respectively, and 136 bps in combination (these numbers are the sums for equities in Exhibit 3). Results are generally similar across other asset classes, adjusting for Baseline weights. The test portfolios consisting of 50% cash and 50% assets also suggest that the results are not attributable to any systematic valuation tendencies that produce a skewed distribution of portfolio weights.

EXHIBIT 3

Return Contribution for Value and Momentum Signals (in basis points)

Asset Class	Value	Momentum	Value + Momentum
U.S. Equities	9	6	34
U.K. Equities	10	7	16
Europe X U.K. Equities	3	15	23
Japan Equities	2	38	52
Pacific X Japan Equities	1	2	5
Canada Equities	0	1	2
EM Equities	3	–1	4
U.S. REITS	23	10	37
Commodities GSCI	12	24	35
U.S. Nominal Treasuries	11	–8	4
U.S. Investment Grade Credit	9	6	16

EXHIBIT 4

Returns for Unconstrained Portfolio, 50% Asset, 50% Cash above Baseline (in basis points)

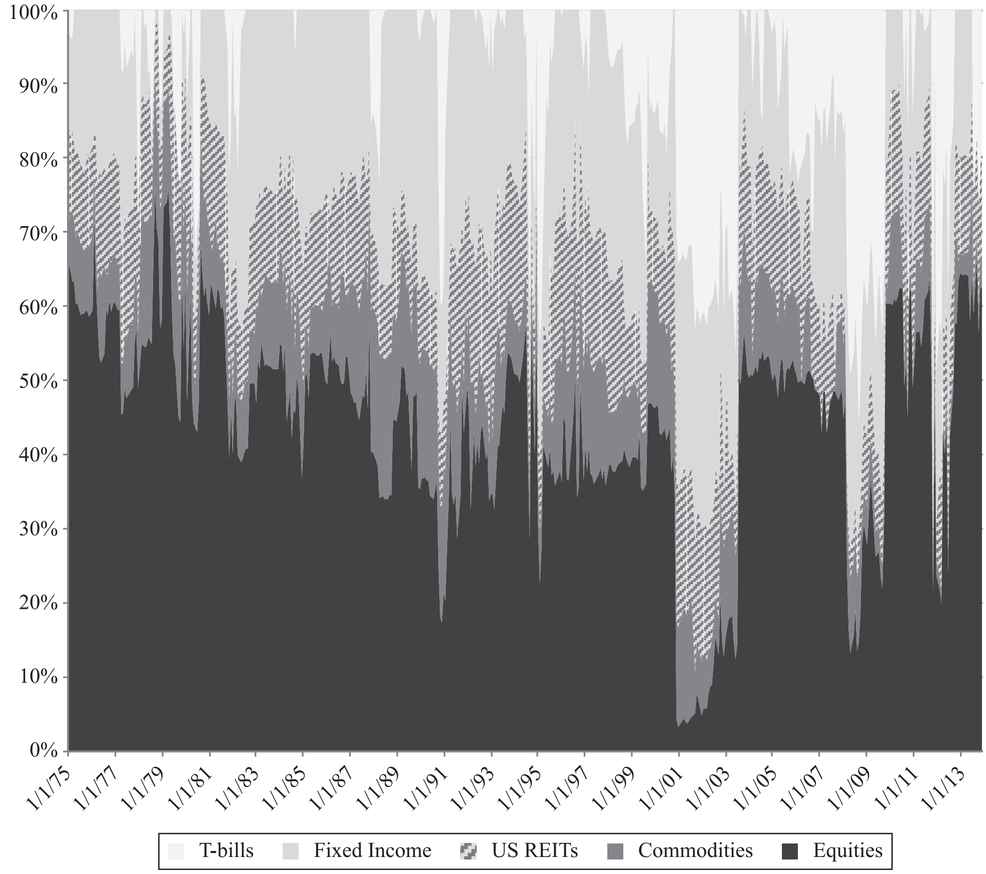
Asset Class	Value	Momentum	Val + Mom
Equities	43	150	194
U.S. REITS	134	112	249
Commodities GSCI	72	95	172
U.S. Nominal Treasuries	36	74	111
U.S. Corporate Bonds	47	112	160

INTERACTION OF VALUE AND MOMENTUM SIGNALS

The composition of the $B + V + M$ portfolio varied considerably through time, as can be seen in Exhibit 5. The highest weighting in equities occurred in the late 1970s and again in July 2009, when the portfolio consisted of about 75% equities. The lowest weighting occurred in January 2001. In the case of July 2009, the high equity weighting did not come until well after the recovery was underway, as a result of a negative momentum signal persisting through the first half of 2009. Similarly, the low equity weighting in January 2001 did not occur until nearly a year after the peak of the NASDAQ in March 2000.

EXHIBIT 5

$B + V + M$ Portfolio Composition, 1975–2013



Periods when value and momentum signals are aligned tend to be followed by periods of abnormally high returns (value cheap and momentum positive) or abnormally low returns (value expensive and momentum negative). To examine this interaction further we analyze our 1926 data set because it offers significantly more instances when the signals are both of the same sign, which is relatively uncommon. We find that periods when value and momentum for U.S. equities were both positive produced subsequent one-year average returns to U.S. equities averaging 14.4%, nearly 800bps above the average return for U.S. equities. Similarly, when both signals were negative, the following one-year average return was –7.6%. In our main 1975–2013 study, the $B + V + M$ portfolio tends to have its best performance relative to Baseline when the Baseline returns are in the tails of the distribution, as can be seen from Exhibit 6. Notice the particularly high average 651bps of outperformance in "bear" markets.

EXHIBIT 6

$B + V + M$ Performance as a Function of Trailing One-Year Baseline Returns, 1975–2013 International Study

Past 1y Baseline Real Ret	Number of Occurrences	Average Outperformance (in bps)
< –5%	51	651
–5% to 5%	150	188
5% to 15%	190	191
15% to 25%	44	133
> 25%	22	266

The realized correlation between the value and momentum signals for each major asset class from 1975 to 2013 can be found in Exhibit 7.[6] The prior belief that they would be negatively correlated is borne out in the data and dovetails with the cross-sectional findings of Asness, Moskowitz, and Pedersen [2013], notwithstanding the exception of Japanese equities. We can see

EXHIBIT 7

Correlation of Value and Momentum Signals, 1975–2013 International Study

Asset	Correlation Coefficient
U.S. Equities	–.18
U.K. Equities	–.19
Europe X U.K. Equities	–.29
Japan Equities	.19
Pacific X Japan Equities	–.46
Canada Equities	–.28
EM Equities	–.33
U.S. REITS	–.30
Commodities GSCI	–.22
U.S. Nominal Treasuries	–.08
U.S. Credit	–.03

that value and momentum are complementary in a portfolio context: the improvement in the return of the $B + V + M$ is greater than the sum of the return enhancements from the $B + V$ and the $B + M$ portfolios. For example, in our main international study (1975–2013), the enhancement from value and momentum working together in the $B + V + M$ portfolio is 266bps, while Value on its own adds 86bps and Momentum on its own adds 155bps, summing to 241bps. This is largely due to the way the value and momentum signals interact with the leverage constraint; as shown in Exhibit 4, when we take away the leverage constraint, the enhancements from Value and Momentum measured separately come close to adding up to the enhancements from the Value plus Momentum portfolio with both signals combined.

Exhibit 8 shows that value and momentum working together at the asset class level have consistently added to returns for each of the past nine decades studied.

RISK

We examined a number of risk metrics, including standard deviation of monthly returns as well as largest drawdowns over one- and five-year periods. All of these statistics are depicted in Exhibit 9. In all five studies, B + V + M portfolios show higher returns, higher Sharpe ratios, and lower maximum one-year drawdowns compared to the relevant Baseline portfolio. These results are perhaps even more striking if we consider that the least risky way to hold a given exposure through time is to maintain a constant weight—and therefore any dynamic scaling strategy has to overcome this headwind. For example, owning \$100 of equities for the first six months of every year and \$100 in T-bills for the second six months is riskier than holding \$50 of equities and \$50 of T-bills for the whole year.[7]

The increase in Sharpe ratio from the Baseline to the $B + V + M$ portfolios is encouraging. However investors may be even more concerned about large drawdowns over longer-term horizons, which are not captured by Sharpe ratios. Viewed from this perspective, the $B + V + M$ is less risky than the static Baseline portfolio. For example, the worst five-year drawdown for the $B + V + M$ portfolio is a gain of 2.5%, compared to a loss of 18.6% for the Baseline portfolio during its worst five-year stretch. Using momentum as a stand-alone factor reduced the worst one- and five-year drawdowns

EXHIBIT 8

Decade-by-Decade Performance of Value- and Momentum-Based Scaling (returns for each strategy portfolio in bps)

	Decade	Baseline	Val vs. Baseline	Mom vs. Baseline	Val + Mom vs. Baseline
Study 3	01/30/1926–12/31/1934	8.09%	131	359	409
Intnl (1926)	12/31/1934–12/31/1944	3.68%	140	89	262
	12/31/1944–12/31/1954	4.24%	219	145	283
	12/31/1954–12/31/1964	8.65%	167	198	344
	12/31/1964–12/31/1974	–0.82%	–62	317	264
Study 1	12/31/1974–12/31/1984	4.98%	172	26	228
Intnl (1975)	12/31/1984–12/31/1994	8.55%	87	182	222
	12/31/1994–12/31/2004	6.26%	29	261	358
	12/31/2004–12/31/2013	3.09%	52	155	254

Exhibit 9

Portfolio Performance Statistics (real annual returns, except for worst 5-year that are total returns)

		Results of Studies			
		Baseline	**Value**	**Momentum**	**Val + Mom**
Study 1	Mean Return	5.77%	6.63%	7.32%	8.43%
Intnl (1975)	Stdev	9.05%	9.09%	9.09%	9.17%
	Sharpe	.50	.59	.67	.78
	Worst 1-Yr	–35.4%	–34.0%	–23.1%	–20.2%
	Worst 5-Yr	–18.6%	–21.4%	–5.6%	2.5%
	Worst 1-Yr vs Baseline	NA	–5.7%	–16.7%	–7.8%
	Worst 5-Yr vs Baseline	NA	–16.5%	–8.5%	–1.4%
Study 2	Mean Return	5.28%	6.38%	6.87%	7.94%
Equal Weights	Stdev	7.89%	8.62%	8.51%	8.87%
	Sharpe	.51	.60	.66	.76
	Worst 1-Yr	–35.1%	–34.2%	–24.4%	–23.2%
	Worst 5-Yr	–18.6%	–20.7%	–0.7%	3.7%
	Worst 1-Yr vs Baseline	NA	–5.6%	–13.9%	–4.7%
	Worst 5-Yr vs Baseline	NA	–9.9%	–2.8%	4.3%
US Only	Return	6.35%	6.56%	6.50%	7.04%
1975	StDev	10.28%	10.30%	9.83%	10.07%
	Sharpe	.50	.52	.54	.58
	Worst 1-Yr	–28.4%	–29.4%	–20.1%	–17.9%
	Worst 5-Yr	–21.4%	–24.1%	–23.5%	–20.2%
	Worst 1-Yr vs Baseline	NA	–13.8%	–10.2%	–14.4%
	Worst 5-Yr vs Baseline	NA	–57.2%	–21.3%	–36.5%
US Only	Return	5.37%	5.95%	6.29%	7.11%
1926	StDev	15.04%	17.89%	12.78%	15.37%
	Sharpe	.35	.33	.48	.45
	Worst 1-Yr	–44.4%	–54.4%	–24.1%	–37.5%
	Worst 5-Yr	–31.4%	–37.6%	–34.0%	–27.1%
	Worst 1-Yr vs Baseline	NA	–15.1%	–62.2%	–14.7%
	Worst 5-Yr vs Baseline	NA	–62.0%	–62.6%	–38.1%
Intnl	Return	5.46%	6.28%	6.84%	7.62%
1926	StDev	10.35%	12.87%	9.42%	11.10%
	Sharpe	.47	.44	.66	.63
	Worst 1-Yr	–36.8%	–44.4%	–21.6%	–31.0%
	Worst 5-Yr	–24.4%	–34.1%	–25.4%	–26.7%
	Worst 1-Yr vs Baseline	NA	–9.3%	–34.2%	–16.9%
	Worst 5-Yr vs Baseline	NA	–33.4%	–24.5%	–20.3%

significantly. Value, on the other hand, experienced more significant drawdowns over one-year horizons in most of the portfolios.

Nonetheless, it is sobering to note that in the longer-dated studies, the $B + V + M$ portfolio suffers periods of significant underperformance versus the static-weight Baseline, as can be seen in Exhibit 9. This is particularly the case for portfolios consisting solely of U.S. assets, showing that international diversification is a significant component of the historical return pattern delivered by value- and momentum-based dynamic scaling. Also, the worst loss figures versus Baseline underscore the negative correlation between value and momentum signals. For example, in the U.S.-only study (1926–2013), we see that the worst relative loss from value for the one-year horizon was 15.1%, and the worst loss from momentum was 62.2% (June 1932–1933); however, for the $B + V + M$ portfolio, the worse one-year relative loss was only 14.7%.

CAVEATS

Although the results we present are not the result of a search for optimal parameters, we still found it important to perform robustness tests and outline important caveats. As mentioned above, we perturb the valuation-centering points on the earnings yield for equities and REITs by 200bps and present our findings in Exhibit 10. Not surprisingly, the return was impacted by the change in centering points; however, the portfolios still experienced a significant improvement in return and risk.

We tested two more alternative centering points for equities in our main international study (1975–2013) by replacing the 6% level for all equity markets (and REITs) with a simple average of the last 25 and last 50 years' inflation-adjusted earnings yield (based on the prior 10 years of earnings) of the U.S. market. As a result of this change, the extra return from value-based scaling was reduced by about half—from 86bps to 45bps using the past 25-year average and from 86bps to 39bps using the past 50-year average. The $B + V + M$ dynamic portfolio returns were reduced by about 35bps, but the enhancement relative to the static portfolio is still statistically significant.[8]

For U.S. Treasuries, we examined the following three signals: 1) current level of interest rate forward (20-year five years forward) compared to its average over the past 10 years, 2) current short-term rate compared with average inflation over the past three years, and 3) the current level of the short-term rate compared to its level six months ago. All three alternative measures enhance the predictive value of the signal.

We tested an alternative momentum metric that is more commonly used by practitioners—namely the current period total return index compared to the average inflation-adjusted total return index over the last 12 months. The fixed point, 12-1 month lagged metric that we employed removes the impact of seasonality, but introduces reference point sensitivity, in which a single data point can have an outsized impact on the signal. The difference in risk and returns between these two metrics was insignificant. We also tested the use of a small hurdle for momentum (because all asset classes tend to have positive momentum when measured on a nominal, total return basis) and a no-trade region (if the asset price was close to its reference point). We found that neither adjustment had a material impact on risk or returns.

We built portfolios with Baseline weights that can be scaled up to 2/3 for value and 1/3 for momentum. This results in more balance between value and momentum-based scaling than is the case with a 50/50 weighting scheme. The momentum signal is binary, whereas the value signal is continuous and proportional to the strength of the signal. Thus, the average absolute size of the value signal is often much less than its maximum of plus or minus 2/3, and closer to the plus or minus 1/3 of the momentum signal. The 2/3:1/3 weighting scheme underperforms the 50/50 scheme by 35bps per annum, which is largely attributable to momentum outperforming valuation-based scaling in the majority of asset classes.

TRANSACTIONS COSTS AND TURNOVER

We ignore transaction costs in all of our historical studies. We do, however, measure turnover, which should give a sense of the return impact based on estimates for past levels of transaction costs. Currently, transactions costs in ETFs and index funds are very low, which is beneficial for the dynamic asset allocation approach presented in this article. The annual portfolio turnover for the Baseline portfolio is roughly 15%, which arises from the monthly rebalancing back to fixed weights. The turnover for the $B + V$ portfolio was roughly 70% and the turnover for the $B + V + M$ portfolio was just over 100% per annum.[9]

EXHIBIT 10

Perturbed Equity and REIT Valuation-Centering Points (D/P for REITs)

Portfolio		E/P 8%	E/P 7%	E/P 6%	E/P 5%	E/P 4%
B + V	Mean Return	5.98%	6.31%	6.63%	6.93%	7.22%
Intnl (1975)	Stdev	7.87%	8.44%	9.09%	9.78%	10.49%
	Sharpe	.60	.60	.59	.58	.57
B + V + M	Mean Return	7.93%	8.22%	8.43%	8.55%	8.57%
Intnl (1975)	Stdev	8.31%	8.73%	9.17%	9.59%	10.02%
	Sharpe	.81	.80	.78	.76	.73

CONCLUSIONS

We find that using simple measures of valuation and momentum to dynamically adjust asset allocation has historically produced superior investment returns compared to a more static investment strategy. In both post-1975 studies, we find that a strategy employing value and momentum together provides higher quality returns than using either value or momentum alone. This can be attributed to negative correlation and the general complementary nature of value and momentum.

This research is distinctive in that we explore the effects of value and momentum at the asset class level in a form that should be practical for any investor to implement using low-cost index funds and ETFs. The existing body of research on value and momentum has been focused at the level of individual securities within asset classes—or to the extent it has been reviewed in the context of asset allocation, it has generally taken the form of higher-turnover strategies requiring leverage and shorting.

Should we expect dynamic asset allocation based on asset class level valuation and momentum factors to continue to offer superior returns? Three significant forces that shape asset price dynamics (beyond fundamental changes in future cash flows) are likely responsible for the results of our studies.

First, time-varying risk dynamics present opportunities to increase allocations to risky assets when perceived risk is high or investor risk aversion has increased and expected returns are elevated. This is now generally viewed as a rational feature of markets and has been shown across asset classes. Hence, it should be possible for an asset allocation approach that dynamically adjusts allocations based on expected returns (as signaled by asset valuations) to earn a higher expected return than a static allocation approach, although it may also be subject to higher risk.

Second, value investing benefits from prices that periodically diverge from intrinsic value.[10] This is a behavioral rather than a risk premium-based source of return; and it is partially explained by academic research showing that people are subject to a variety of decision-making biases in the presence of uncertainty that are hard to eradicate, even with self-knowledge.[11] Although many value-based investors view trend-following as the antithesis of their approach, it may well be that the existence of momentum often accounts for the very opportunities that value investors seek to exploit.

Momentum is "the premier anomaly" according to Fama and French [2008]. Their study focuses on cross-sectional momentum across single stocks. If anything, its "cousin," time-series momentum or trend-following, has been even more successful and a bigger challenge for finance theories. Hurst, Ooi, and Pedersen [2012] demonstrate that trend-following strategies were profitable in every major financial crisis over the past hundred years, while adding to overall portfolio returns. If momentum investing is risk reducing, we would expect it to have a negative risk premium.[12] Although most inefficiencies in financial markets are localized enough that dedicated capital can make them disappear, some might require so much capital, or the risk-adjusted returns to dedicated capital might be so low, that they should not be expected to disappear. Momentum at the asset class level might be one such large scale anomaly, with sufficiently deep-seated behavioral underpinnings that it might not disappear even with widespread awareness of its existence.

It would be useful to expand the case study to explore the impact of including a broader range of readily available sources of risk premium—such as small-capitalization equities, value stocks (those with relatively low Price/Book ratios), high-yield bonds, non-U.S. investment-grade debt, emerging market debt, individual commodities, and foreign exchange overlays. The interaction between value and momentum at the asset class level with value and momentum at the individual security (cross-sectional) level would be another fascinating avenue of further research. Although we attempt to mitigate the pernicious effects of backtest bias, future studies could improve upon our approach by using data available contemporaneously with the asset allocation decision.

Investors are increasingly questioning the paradigm of a static strategic asset-allocation approach based on market capitalization. We hope that our research answers some of the questions being raised and sheds light on others that are worth asking.

APPENDIX

Metrics for Value

We chose a single, basic metric (e.g., a cyclically adjusted earning yield for each broad equity market) as a valuation measure for each asset. We then selected a centering point for each valuation metric that represented adequate compensation for bearing the systematic risk of that asset class. In each case, we attempted to use a valuation metric and centering point that an investor might reasonably have used over the sample period without the benefit of foresight. Centering points were not based on the entire in-sample mean value of the metric chosen. Once we chose the valuation metric and centering point, we did not seek to optimize its parameterization or form, but rather kept it constant, thereby attempting to reduce look-ahead bias. Valuation-based scaling is set equal to the percentage deviation from the fair value centering point for each asset class. Below is a description of the metrics used for valuation-based scaling for each asset class, which is also summarized in Exhibit 1.

- **Equities**: We used the Shiller earnings yield (E/P) where E is the average of the past 10 years of inflation-adjusted corporate earnings on that index and *P* is the current stock market index level. We used a centering point of 6%, which we believe is consistent with a long-term real equity return of 4.5% to 5.5%, given assumptions on long-term real economic growth and its relationship to earnings growth of public companies.[13] For example, if companies pay out 60% of earnings as dividends, and dividends and earnings grow at 1.5% pa (which has been close to the long-term average in the U.S.), then a 6% earnings yield would be consistent with a 5.1% long-term real return. We have long-term data only for the U.S., which showed an average Shiller E/P of 7.0% in the 50 years before 1975. Our main sample of 1975–2013 had an average of 6.2%. Because the previous 50 years included the Great Depression and a World War, it did not seem unreasonable to use 6% rather than the 7% of the tumultuous 1925–1975 period.
- **U.S. 10-year Treasury notes**: We used the 10-year implied real rate, which is the difference between the current yield of the 10-year Treasury note and the next 10-year forecasted inflation (via surveys). We chose a centering point of 3% for the 10-year real yield. This implied real Treasury yield averaged 2.2% in the 50 years before 1975, but 2.7% if we exclude the decade when Treasury yields were capped, and then 2.9% in 1975–2013. We round this up to 3%, given the inflationary environment in the early part of our main sample. This 3% real yield is of course far above recent market levels. The 3% figure represents a combination of expected average real short-term rates and a required term premium.
- **U.S. investment-grade corporate bonds**: We used the credit spread, which is the difference in yield between an index of corporate bonds and the yield on a similar maturity portfolio of U.S. Treasury bonds. We chose 1.5% as the centering point for the credit spread, representing a risk premium of around 1% above a long-term underlying default loss rate of around 0.5%. From 1925 to 1975, this spread averaged roughly 1.7%.
- **U.S. REIT Index**: We used the dividend yield based on average inflation-adjusted dividends from the previous 10 years on the REIT index. We chose a centering point of 6%, which—on the joint assumptions of the dividend being inflation protected and part of the dividend potentially representing a return of capital—is consistent with a real return of 4% to 5%. Although real estate is less risky than the broad equity market, REITs typically hold real estate on a leveraged basis, and hence the centering point for the real return of 4% to 5% is a plausible assumption.
- **Commodities (GSCI Index)**: We used the ratio of the average inflation-adjusted price over the past 10 years to the current spot price. We chose 1.0 as the natural centering point for a mean-reversion metric. We lack a measure of expected cash flows or real yield for commodities.

The reader may question why interest rates do not come into the evaluation of equity market cheapness. The reason is that our approach attempts to rebalance the portfolio based on how much to invest in equities alone, rather than creating a position that is long equities and short bonds. In a scenario in which equities are expensive when viewed in isolation but cheap relative to bonds, and bonds themselves are offering low expected returns, our portfolios would have low exposures to both equities and bonds.

ENDNOTES

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[1]See Soros [1988]. Another model we found compelling was explained in a working paper by De Grauwe and Grimaldi [2003].

[2]All reported returns are inflation-adjusted, geometrically averaged, annually compounded, and do not include transactions costs or withholding taxes.

[3]See Jegadeesh and Titman [1993] and Asness [1995].

[4]We count REITs and Commodities as being more equity-like than bond-like and so include them in the 65% equity bucket.

[5]It is more common in the literature to use continuous value signals and binary momentum signals, probably because

value signals are expected to work better at extremes but this is not necessarily so with momentum signals. We stick with these common choices and leave their underpinnings or alternative choices to future research.

[6]The correlations shown in the table are calculated on the desired deviations in baseline weights indicated by the value and momentum signal for each asset class. We also ran correlations on the signals themselves, and the resultant numbers looked broadly similar.

[7]Generally, risk goes up with the square root of time, so holding 2X the position for half the time tends to be sqrt(2) = 1.41X riskier.

[8]Our measure includes negative earnings, but excludes extra-ordinary and one-off items. In practice it would be appropriate to adjust the earnings yield centering point to each specific market to address differences in accounting practices and other broad characteristics.

[9]All of the aforementioned figures should be thought of as roundtrip turnover (i.e., the sale of one unit of one asset to buy one unit of another asset will be counted as one unit of turnover).

[10]Intrinsic value is often not a fixed value, but rather a value that can be influenced by market price. For instance, rising market prices can have real effects that lead to an increase in intrinsic value.

[11]See the work of Kahneman and Tversky [1974]. For a market practitioner's perspective, read Howard Marks' memo of June 20, 2012, "It's All a Big Mistake."

[12]Investors are fairly rational about this negative risk premium in other contexts; for instance, we observe that out-of-the-money puts on stock indexes appear to be priced above their actuarial value.

[13]For simplicity, we have used the same cyclically adjusted earnings-yield centering point for all global equity markets. Our measure includes negative earnings, but excludes extra-ordinary and one-off items. In practice, it would seem more appropriate to use slightly lower or higher earnings-yield centering points depending on the market, because there are differences in the broad characteristics of each market, as well as accounting practices.

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