ADAPTIVE MULTI-FACTOR ALLOCATION

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EXECUTIVE SUMMARY

An increasing number of institutional investors are implementing factor allocations to target additional sources of returns, manage risk and/or enhance income. While certain single factors have earned a premium over long extended periods, their returns over shorter timescales have been variable. Combining factors through a multi-factor allocation has reduced the variability in performance through diversification and resulted in long-term historical outperformance. However, although factor allocation approaches based on simple diversification techniques such as equal-weight or risk parity are transparent and have performed well historically, some investors, such as valuation-sensitive or macro-sensitive investors, utilize a dynamic approach by adapting their factor allocations to be more consistent with their strategic or tactical asset allocation process. An adaptive approach aims to strike a balance between a pure single factor timing strategy and the diversification effects of a multi-factor allocation strategy. In this paper, we discuss a framework that aims to adapt multi-factor allocations to changing market environments while preserving some of the diversification benefits of multi-factor investing.

We study the performance of factors in various economic regimes and find that incremental returns could have been extracted by adapting factor allocations to the prevailing market environment. We extend our earlier research in combining factors by presenting a multi-faceted approach to adapting allocations across factors based on four pillars: (1) Macro Cycle, (2) Momentum, (3) Valuations and (4) Market Sentiment. Over the sample period (1986-2018), we find that each pillar delivered incremental returns to top-down static equal-weighted multi-factor allocation strategies. Moreover, an approach combining all four pillars brought diversification benefits and more stable returns than single-strategy approaches.

We present our results in the context of (1) a strategic institutional investor with a top-down static allocation to multiple factors (“Strategic Mix“), (2) a strategic institutional investor with a tilt to exploit market cycles (“Adaptive Tilt”) and (3) a tactical institutional investor who tolerates high turnover to seek higher returns (“Adaptive Mix”). We found during the sample period (1986-2018) that an increased allocation, vis-à-vis the Strategic Mix, to the composite four-pillared approach resulted in increased portfolio efficiency.

Finally, we compare and contrast the Adaptive Mix approach based on two alternative portfolio construction methods: (1) using a top-down weighted blend of existing factor indexes and (2) bottom-up security-level optimizations to maximize exposure to targeted factors. We found that from 1999 through 2018,[1] both top-down and bottom-up adaptive

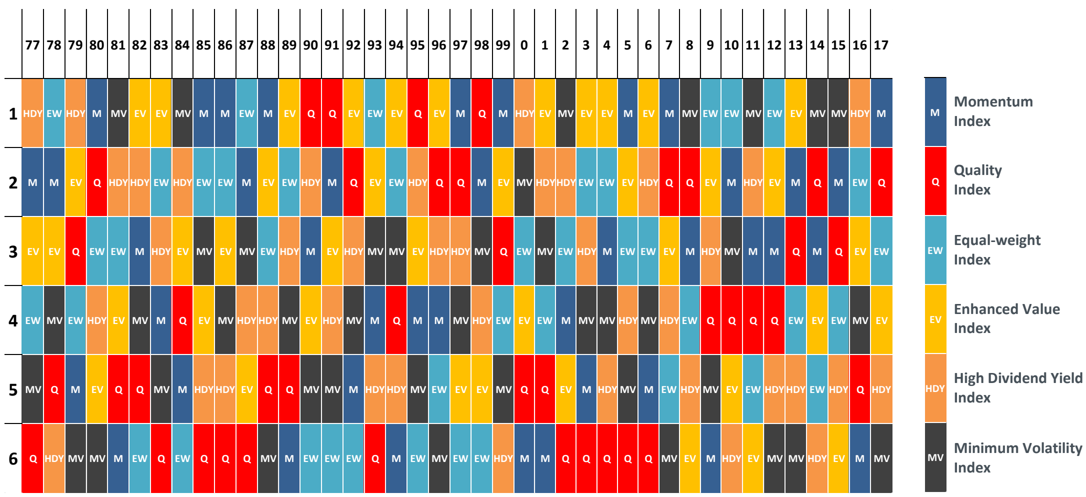
[1] This sample period differs from the one above due to data available for bottom-up security-level optimization.

approaches generated an additional active return with similar risk and higher information ratio vis-à-vis static allocation to multiple factors.

INTRODUCTION

Factor investing has been one of the most widely discussed investment topics since the global financial crisis of 2008, when institutional investors questioned whether their portfolios were adequately diversified. Through extensive research, indexes have been designed and created to support investors as they put theoretical investment concepts into practical and transparent implementable solutions. Institutional investors are using factor indexes as part of their investment process to seek excess returns, manage volatility and/or increase income. MSCI offers a core set of single factor indexes designed to represent the respective performance of the value, momentum, quality, low volatility, low size and dividend yield factors (see Bender et al., 2013).

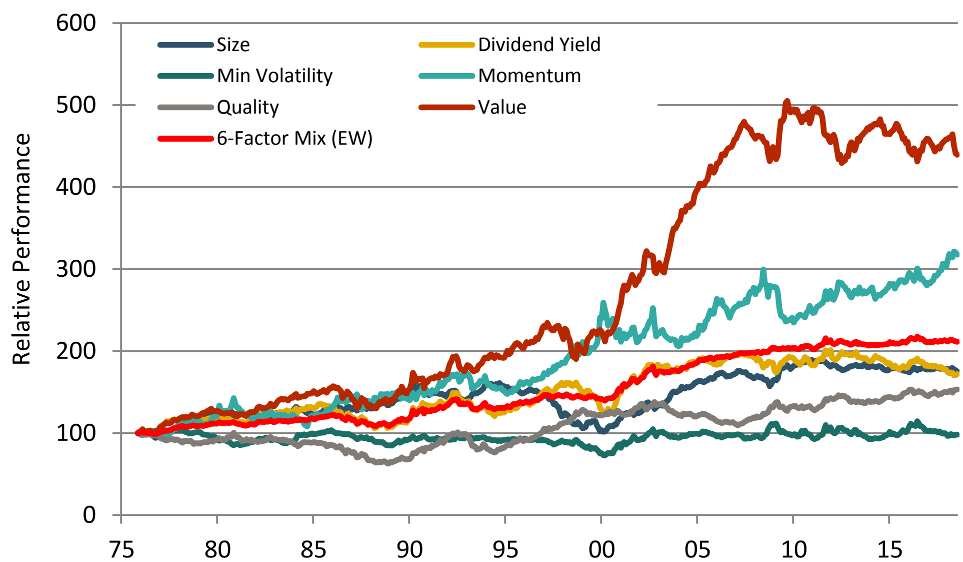
Exhibit 1: Performance of MSCI World factor indexes ranked 1-6 in different time periods



While certain single factors have earned a market premium over long extended periods, their returns over shorter time scales have been cyclical. Exhibit 1 ranks performance of six factor indexes each year since 1977 on a scale of 1-6 (1 the highest, 6 the lowest), illustrating the cyclical nature of performance over short periods. Multi-factor approaches, which combine multiple factors, aim to potentially reduce the cyclicality of individual factor performance through diversification, while (as we see in Exhibit 2) continuing to attain long-term outperformance. MSCI offers statically weighted multi-factor indexes as both top-down blends of single factor indexes and bottom-up multi-factor indexes based on maximizing security level target factor exposures (Doole et al., 2015).[2]

[2] Readers can refer to Kulkarni et al. (2018) for a recent discussion comparing and contrasting top-down and bottom-up approaches to multi-factor construction.

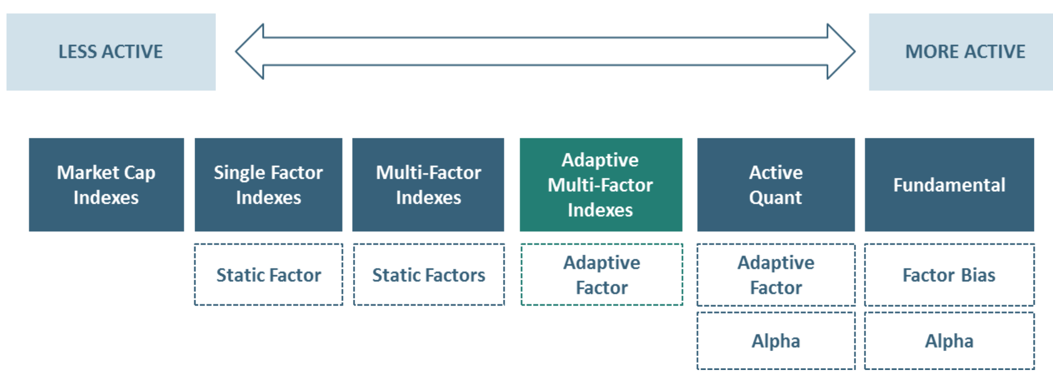
Exhibit 2: Relative performance of single indexes and a multi-factor index to MSCI World



Sample period is January 1977 – June 2018. Factor indexes representing each factor are as follows: MSCI World Equal-weight (Size), MSCI World High Dividend Yield (Dividend Yield), MSCI World Minimum Volatility (Min. Volatility), MSCI World Momentum (Momentum), MSCI World Quality (Quality), MSCI World Enhanced Value (Value).

Adaptive factor allocation has typically been confined to active quant managers. Multi-factor indexes may serve as an additional alternative to passive and active investing (see Exhibit 3).

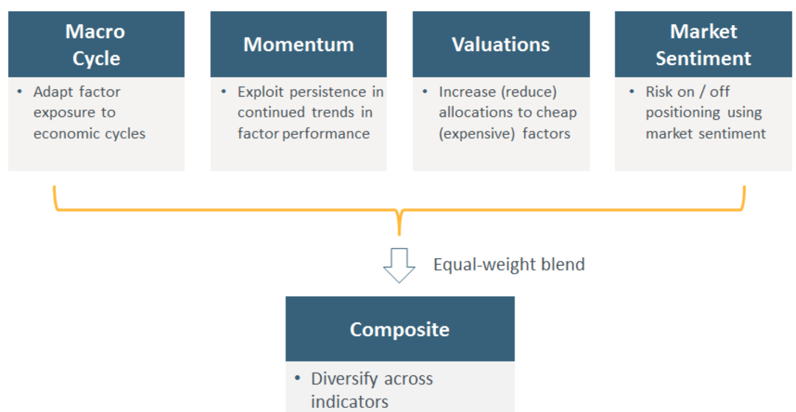
Exhibit 3: Continuum of factor based strategies



With the growing adoption of factors as building blocks for asset allocation, institutional investors are increasingly questioning whether simple diversification across factors (such as equal-weight or risk parity) are the optimal allocation methods, and are asking whether incremental returns can be extracted by exploiting how factors behave across market environments. Our earlier research (Gupta et al., 2014) shows contemporaneous factor performance has varied by economic regime, in particular, by changes in growth and inflation. For example, the value and size factors have tended to be exposed to common macro risks, such as negative growth shocks, while low volatility and quality have tended to have more defensive characteristics. In our paper investigating alternative approaches to combining factors (Alighanbari and Chia, 2014), we show momentum and value effects were not only effective at the stock level, but were also prevalent in the factors themselves. In other words, factors we studied that performed relatively well and/or had valuations lower than historical averages, tended to outperform over medium-term holding periods.

This paper harmonizes and extends our previous work by reviewing a multi-faceted approach to dynamically allocate across factors based on four pillars: (1) Macro Cycle, (2) Momentum, (3) Valuations and (4) Market Sentiment.

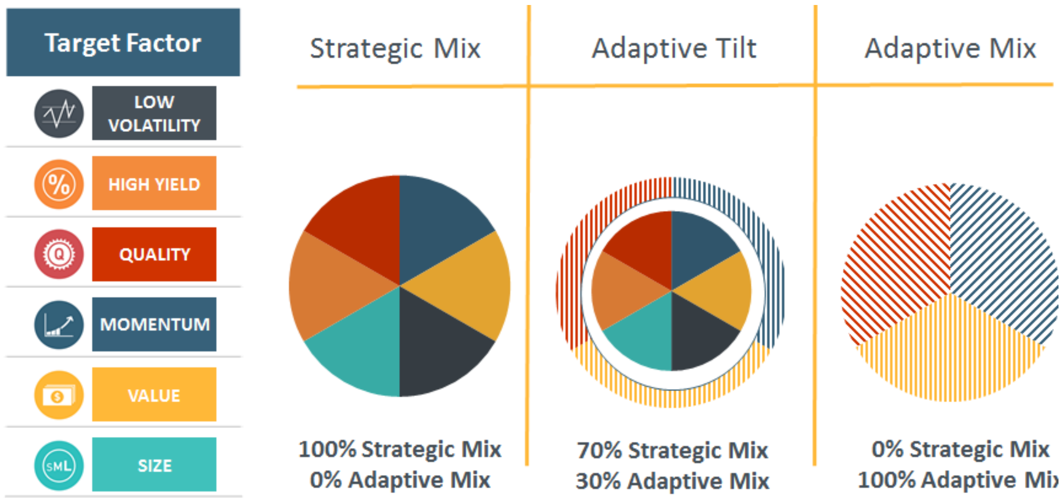
Exhibit 4: A four-pillared approach to adaptive multi-factor allocation



Through historical simulations we observed how each pillar demonstrated incremental returns relative to a simple top-down static equal-weighted mix, and how a multi-strategy approach that combined four pillars into a single strategy added diversification benefits relative to strategies based on a single pillar.

We present our results in the context of (1) a strategic institutional investor with a top-down static allocation to multiple factors ("Strategic Mix"), (2) a strategic institutional investor who would like to tilt their allocations to exploit market cycles ("Adaptive Tilt") and (3) a tactical institutional investor who can tolerate high turnover to seek higher returns ("Adaptive Mix"). This demonstrates a spectrum between strategic and adaptive multi-factor allocations. Exhibit 5 illustrates the three approaches.

Exhibit 5: Three approaches for multi-factor investing[3]



In this paper, we present two sets of results:

1. Top-down static and adaptive allocation factor strategies since 1986 using the MSCI World Index as a case study.
2. A top-down vs. bottom-up comparison of static and adaptive multi-factor strategies since 1999 using the MSCI World Index and the MSCI ACWI Index as case studies.

Both sets of results are based on the same indicators constructed from the four-pillared approach to an adaptive multi-factor allocation. The data from 1975 to 1986 is used to create a time-series valuation indicator. Although the framework uses deep history to compute indicators over multiple market cycles, the top-down vs. bottom-up comparison analysis uses last 20 years to compare performance which is reflective of recent market environment.

[3] Adaptive Mix refers to time varying factor allocations, whereas Strategic Mix refers to static allocations over time.

LITERATURE REVIEW

MACRO CYCLE BASED FACTOR ALLOCATION

Theory suggests that systematic factor returns should be linked to the changing economic/business conditions (Campbell and Diebold, 2009, Fama and French, 1989, Chen Roll Ross, 1986 and Barro, 1990). Positive returns from factors in the long-run have often been associated with being compensated for bearing macroeconomic risk. In our earlier paper – "Index Performance in Changing Economic Environments" -- we showed low size and value have been the most cyclical factor indexes, and low volatility and quality have been the most defensive.

A number of studies have been conducted to use macro-economic indicators to predict excess returns from factor strategies. Ahemerkamp et al. (2012) studied the predictability in carry and momentum strategies across asset classes and found that business cycle indicators have a strong explanatory power. Cooper et al. (2016) proposed a global macroeconomic risk model for value and momentum and found that a meaningful relationship between predicted expected returns and actual average returns across asset classes. In contrast, Asness et al. (2013) found only modest links between factor returns to macroeconomic variables, such as, the business cycle, consumption and default risk.

More recently, Blin et al. (2016) investigated the question of allocation across a range of alternative risk premia strategies and designed an active macro risk-based framework that aims to exploit varying behavior in different macro regimes using point-in-time signals related to nowcasting indicators.

MOMENTUM BASED FACTOR ALLOCATION

Momentum strategies are persistent, pervasive, and well documented from individual stocks, countries and sectors, and are present within a range of asset classes (e.g., Moskowitz et al. 2013). Relatively few studies on adaptive factor allocation have considered the momentum effect on factors themselves. Tibbs et al. (2008) performed a study on the momentum effect amongst style indexes and found outperformance on both absolute and risk-adjusted bases, with long minus short portfolios generating an average 9.25% annual return over a 34-year sample period. More recently, Alighanbari et al. (2014) applied momentum to a wider range of factor indexes and found outperformance over equal-weight strategies over a 40-year period, albeit with relatively much higher turnover.

VALUATION BASED FACTOR ALLOCATION

The use of valuations is at the cornerstone of investing and has been applied in practice for several decades. Although the effectiveness of valuations may be more limited in the short-term, they have caught the attention of long-horizon investors. It is one of the few, if not the only, strategy to compare market prices to fundamental anchors. In the context of multi-factor investing, should a particular factor become crowded, “expensive,” or on the other hand, “unloved,” valuation indicators could have been used to scale back or scale up allocations.

A number of studies have used valuations for factor allocations. Mehmet et al. (2015) and Bonne el al. (2018) used valuation dispersion, amongst other signals to identify crowding effects in factors. Asness et al. (2000) found valuation spreads and earnings growth spreads as important indicators of the attractiveness of value versus growth. Alighanbari et al. (2014) showed incremental returns by scaling factor allocations according to time-series valuations, i.e., using the valuation spread of a factor index relative to the market capitalization weighted index in a historical context. In similar spirit, more recently, Hodges et al. (2017) showed merit in blending cash flow to operating income with the one-year-forward earnings yield as measures of factor valuations. They view the factor as relatively cheap when it has a low valuation relative to its history and to other factors.

However, most recently, Asness et al. (2018) expressed how contrarian factor timing is deceptively difficult. The authors used out-of-sample z-scores calculated from the current book-to-price spread of highly rank vs low ranked stocks for each factor in the context of its *own* history and found there is insufficient evidence for using value as a timing signal. They also noted if the value signal is strong then it may correlate with the value factor itself (increase overlap in value stocks).

More broadly, Yara et al. (2018) examined the relationship of the value spread to value factor returns in equities, commodities, currencies and bonds, and found that returns to value strategies could have been predicted to some extent by the value spread across all the asset classes.

MARKET SENTIMENT BASED FACTOR ALLOCATION

The quant crisis of 2007 and the 2008 global financial crisis characterized by extreme volatility are stark reminders of times when some factor strategies experienced significant losses. Losses in momentum strategies, in particular, have coincided with changing volatility environments. Wang and Xu (2010) investigated the time-variation in momentum profitability and concluded that market volatility has significant power to forecast momentum payoffs, and is more robust than conditioning on business cycle variables.

Market measures, such as the CBOE Volatility Index (VIX), or changes in these measures, have been found to be statistically significant leading indicators of factor performance. Copeland and Copeland (1999) found on days that followed increases in the VIX, portfolios of large-capitalization stocks outperformed portfolios of small-capitalization stocks and value-based portfolios outperformed growth-based portfolios. On the days following declines in the VIX, the opposite effect has occurred. Boscaljon et al. (2011) found evidence supporting their study for holding periods of 30 days or more. Banerjee et al. (2007) examined portfolios sorted on book-to-market equity, size and beta and found VIX-related variables had strong predictive ability.

METHODOLOGY AND SIMULATION RESULTS – FOUR PILLARS

Our dataset is composed of six high exposure factor indexes across the MSCI World Index with history extending back over 40 years (November 1975 – June 2018).[4] Having such an extensive history to review can provide new insights into the behavior of factor indexes along various perspectives.

In this section, we define time-series, cross-sectional and state-based reference indicators for each of the four pillars – (1) Macro Cycle, (2) Momentum, (3) Valuations and (4) Market Sentiment – and then present performance statistics of monthly rebalanced top-down multi-factor portfolio strategies based on these pillars. The strategies we have considered are:

1. Strategies composed of single indicators within each pillar
2. "Integrated" strategies represented by multiple indicators within each pillar
3. Multi-strategy approach that combines the four pillars using an equally weighted blend

In each case, we present the average annualized total return, active return, active risk, information ratio and one-way turnover as part of the performance statistics. To examine performance over time, we plot, along with performance matrix, the cumulative monthly performance of active returns.

MACRO CYCLE PILLAR – METHODOLOGY AND SIMULATIONS

We have investigated a range of macro indicators that are a proxy for economic growth. The indicators are used to classify the state of the economy, so that a pre-defined top-down multi-factor mix can be constructed. For example, during a slowdown, which could be characterized by deteriorating economic conditions, yet continued positive economic growth, a defensive factor mix maybe more appropriate than a cyclical factor mix. On the contrary, during an expansion phase, a cyclical factor mix could be preferred.

The macro indicators we have considered are as follows:

- Organization for Economic Development's (OECD) Composite Leading Indicator (CLI) – a measure of the overall state of the economy, or point in the business cycle.
- US ISM Purchasing Managers Index (PMI) – an indicator of the economic health of the manufacturing sector, issued on the first business day of each month.

[4] Although the data extends back to Nov1975, the simulation results are presented since January 1986. [NOTE: WHY?] The history from 1975 and 1986 is used to build the valuation indicators. The simulations results for ACWI since January 1999 can be found in the Appendix, starting on page 32.

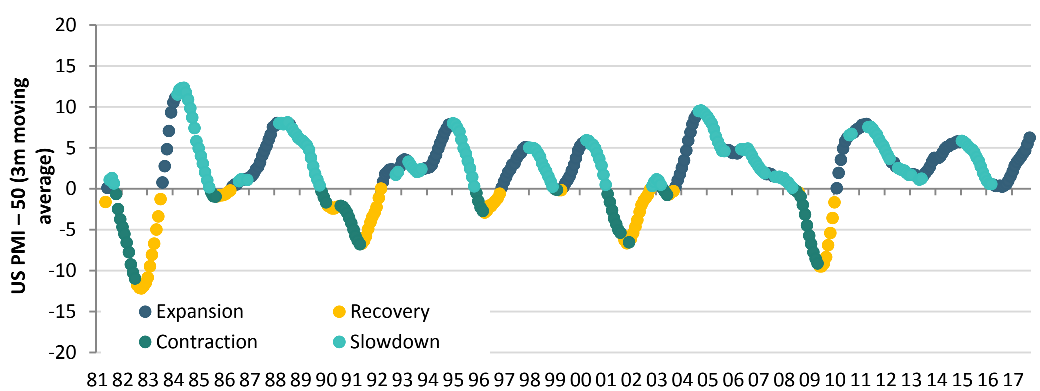
- The Chicago Fed National Activity Index (CFNAI) - a monthly summary of U.S. economic growth, based on a weighted average of 85 indicators of U.S. economic activity weighted to capture the relative importance to historical fluctuations.
- The Federal Reserve Bank of Philadelphia ADS Index – released weekly, the index is designed to track real business conditions at high frequency. It blends high- and low- frequency information as well as stock and flow data.

Although the choice of macro indicators are USA centric and may not be a 1:1 reflection of global economics, they have been selected based on the extensive history available to conduct this study. In practice, global indicators could be more appropriate references.

One of the key differences amongst the macro indicators is the amount of lag between the underlying data referenced to calculate the index and the release date. For example, the CLI has a lag of two months and is published monthly, whereas the ADS adjusts for new information on a weekly basis.

To determine the economic regime, we define four states that characterize the prevailing market environment using the above macro indicators. Each state is defined based on the 3-month vs 12-month moving average of the macro indicator. The plot in Exhibit 6 applies the states to the PMI for illustrative purposes and the table summarizes the macro states.

Exhibit 6: Mapping macro indicators onto macro states, illustration on PMI



Macro State	Macro Indicator
Recovery	Below long-term trend and has been improving
Expansion	Above long-term trend and has been accelerating
Slow Down	Above long-term trend and has been reversing
Contraction	Below long-term trend and has been deteriorating

For each state, we allocate to three out of the possible six factors – top-down equally weighted and rebalanced on a monthly basis (see Exhibit 7). For example, during the Contraction phase, the allocations have a defensive bias with low volatility, quality and value (i.e., a "Quality Mix," see Gupta and Subramanian (2014)), whereas during the Expansion phase, the allocations are momentum, low size and value.

Exhibit 7: Adapting multi-factor allocations to the macro cycle

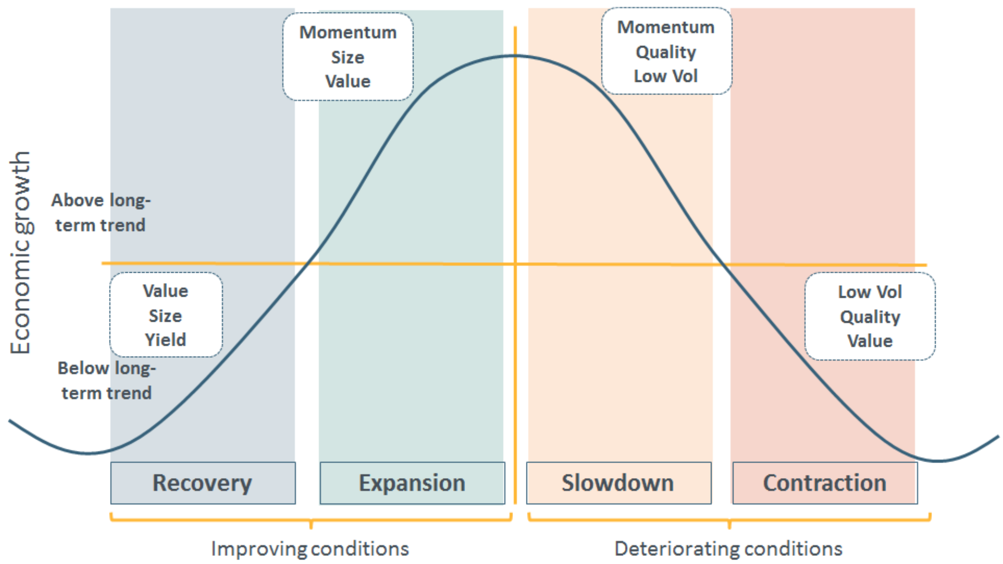
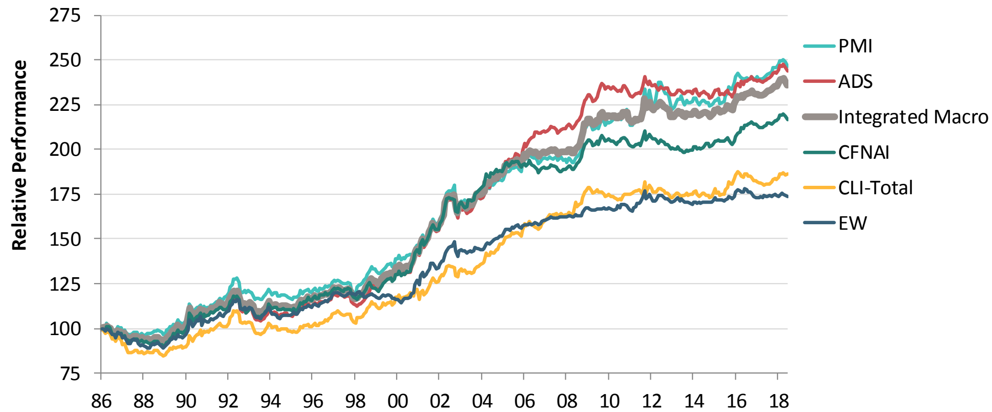


Exhibit 8: Performance of multi-factor simulated strategies using macro indicators



Metrics	MSCI World	EW	ADS	CFNAI	PMI	CLI-Total	Integrated Macro
Total Return (Ann.)	9.88%	11.65%	12.71%	12.35%	12.76%	11.89%	12.76%
Volatility (Ann.)	14.97%	13.77%	14.32%	14.11%	13.89%	14.14%	13.91%
Sharpe Ratio	0.66	0.85	0.89	0.88	0.92	0.84	0.92
Active Return (Ann.)		**1.77%**	**2.83%**	**2.46%**	**2.88%**	**2.00%**	**2.72%**
Active Risk (Ann.)		3.61%	3.94%	4.00%	4.28%	4.13%	3.82%
Information Ratio		**0.49**	**0.72**	**0.62**	**0.67**	**0.48**	**0.71**
Index Level Turnover (1-Way, Ann.)		6.9%	195%	182%	111%	75%	147%

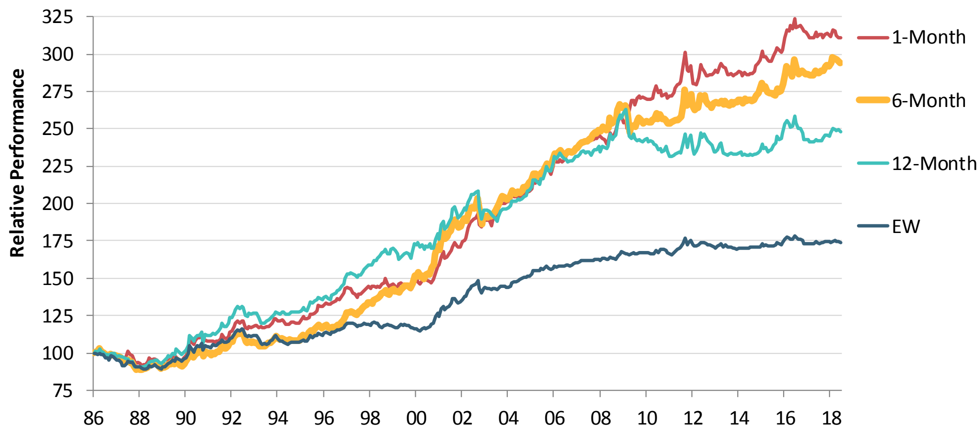
Performance statistics computed in the global MSCI World Standard universe. Simulated portfolios are constructed with equal weighting of factors and monthly rebalancing. Active return and risk are computed relative to MSCI World Index. Information Ratio is defined as annualized active return/annualized active risk. Turnover is calculated as one-way average annualized turnover across all rebalancing. Sample period is January 1986 – June 2018.

As we see in Exhibit 8 and A1, the best-performing macro indicators were ADS, CFNAI and PMI in both the MSCI World Index and the MSCI ACWI Index and form the basis of our integrated Macro Cycle simulated portfolio. We constructed the Integrated Macro Cycle simulated portfolio by equally weighting simulated portfolios of ADS, CFNAI and PMI indicators.

MOMENTUM PILLAR – METHODOLOGY AND SIMULATIONS

The momentum indicators are based on the last 12-, 6- and 1-month historical total returns of an individual factor index. Indexes are ranked on a cross-sectional basis and the top three are combined, top-down equally-weighted and rebalanced monthly.

Exhibit 9: Performance of multi-factor simulated strategies using momentum indicators



Metrics	MSCI World	EW	1-Month	6-Month	12-Month
Total Return (Ann.)	9.88%	11.65%	13.51%	13.33%	12.82%
Volatility (Ann.)	14.97%	13.77%	14.08%	13.90%	13.86%
Sharpe Ratio	0.66	0.85	0.96	0.96	0.92
Active Return (Ann.)		**1.77%**	**3.63%**	**3.45%**	**2.93%**
Active Risk (Ann.)		3.61%	4.89%	4.88%	5.07%
Information Ratio		**0.49**	**0.74**	**0.71**	**0.58**
Index Level Turnover (1-Way, Ann.)		6.9%	547%	201%	161%

Performance statistics computed in the global MSCI World Standard universe. Simulated portfolios are constructed with equal weighting of factors and monthly rebalancing. Active return and risk are computed relative to MSCI World Index. Information Ratio is defined as annualized active return/annualized active risk. Turnover is calculated as one-way average annualized turnover across all rebalancing. Sample period is January 1986 – June 2018.

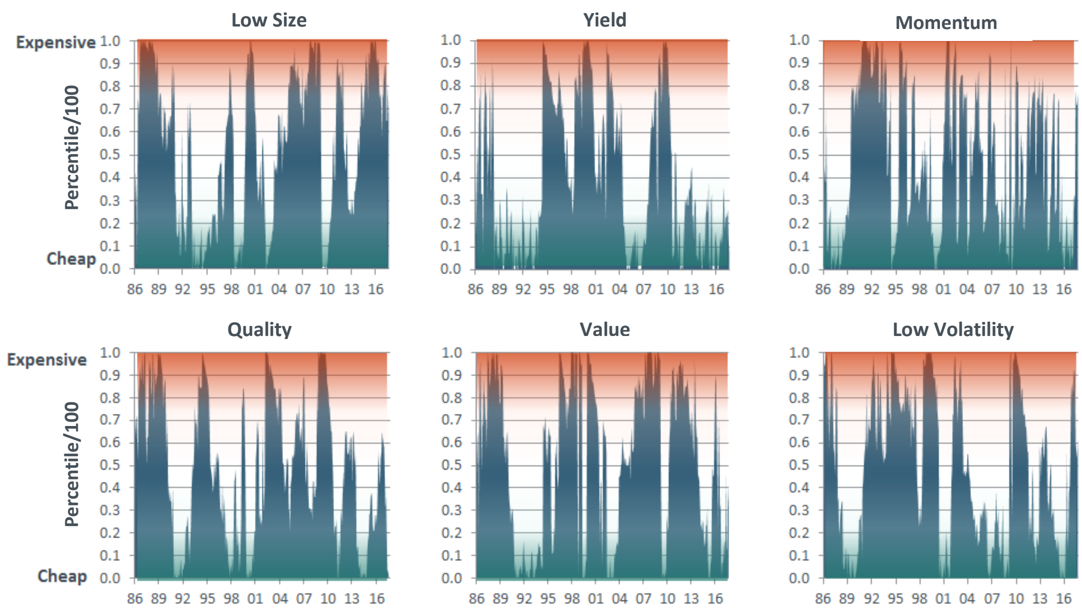
In Exhibit 9 and A2, we see that all three momentum-based indicators performed well vis-à-vis performance of a top-down equally weighted factor simulated portfolio. The best-performing momentum based simulated portfolio, with consideration of manageable turnover, for both the MSCI World Index and the MSCI ACWI Index was 6-month momentum. As such, we constructed the Integrated Momentum-based adaptive simulated portfolio by fully allocating to a 6-month momentum simulated portfolio.

VALUATION PILLAR – METHODOLOGY AND SIMULATIONS

To assess whether a factor index is expensive or cheap, we use time-series valuation, i.e., compare the prevailing valuation spreads in the context of its own history. The valuation spread is computed as the valuation of the factor index relative to the valuation of a *six-*

factor equally weighted mix.[5] So a value index is not overweight simply due to its absolute valuation being structurally lower than other indexes,[6] but would be if its current valuation relative to the six-factor index is significantly below its long-term average. In this study, we consider the following valuation measures to compute valuation spreads – price-to-earnings (P/E), price-to-book (P/B) and price-cash earnings (P/CE). In each case, indexes are ranked on a monthly basis, and the three indexes with the lowest valuations are selected and equal-weighted. Exhibit 10 illustrates how the valuation of factor indexes varies over time.

Exhibit 10: Valuation indicator of factor indexes based on the percentile of price/earnings spread to an equally weighted factor index mix

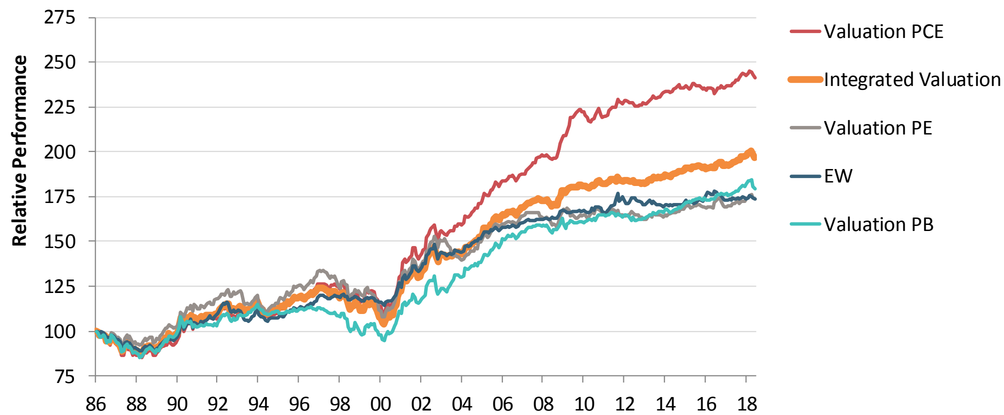


Sample period January 1986 – September 2017.

[5] Note this is different to computing valuation spreads of each factor index relative to its own history, as per Asness (2018).

[6] Which would be the case if we applied cross-sectional valuation amongst the factor indexes.

Exhibit 11: Performance of multi-factor simulated strategies using valuation based indicators



Metrics	MSCI World	EW	Valuation (P/E)	Valuation (P/CE)	Valuation (P/B)	Integrated Valuation
Total Return (Ann.)	9.88%	11.65%	11.69%	12.71%	11.79%	12.06%
Volatility (Ann.)	14.97%	13.77%	13.96%	14.24%	14.56%	14.16%
Sharpe Ratio	0.66	0.85	0.84	0.89	0.81	0.85
Active Return (Ann.)		**1.77%**	**1.80%**	**2.82%**	**1.90%**	**2.18%**
Active Risk (Ann.)		3.61%	4.62%	4.58%	4.43%	4.26%
Information Ratio		**0.49**	**0.39**	**0.62**	**0.43**	**0.51**
Index Level Turnover (1-Way, Ann.)		6.9%	130%	90%	83%	97%

Performance statistics computed in the global MSCI World Standard universe. Simulated portfolios are constructed with equal weighting of factors and monthly rebalancing. Active return and risk are computed relative to MSCI World Index. Information Ratio is defined as annualized active return/annualized active risk. Turnover is calculated as one-way average annualized turnover across all rebalancing. Sample period is January 1986 – June 2018.

In Exhibit 11 and A3, we see the best-performing valuation indicators are P/CE and P/B in both the MSCI World Index and the MSCI ACWI Index. Although P/E does not add return in the long-run we include it for diversification reasons. Overall, we constructed the Integrated Valuation simulated portfolio by equally weighting portfolios of P/E, P/CE and P/B indicators.

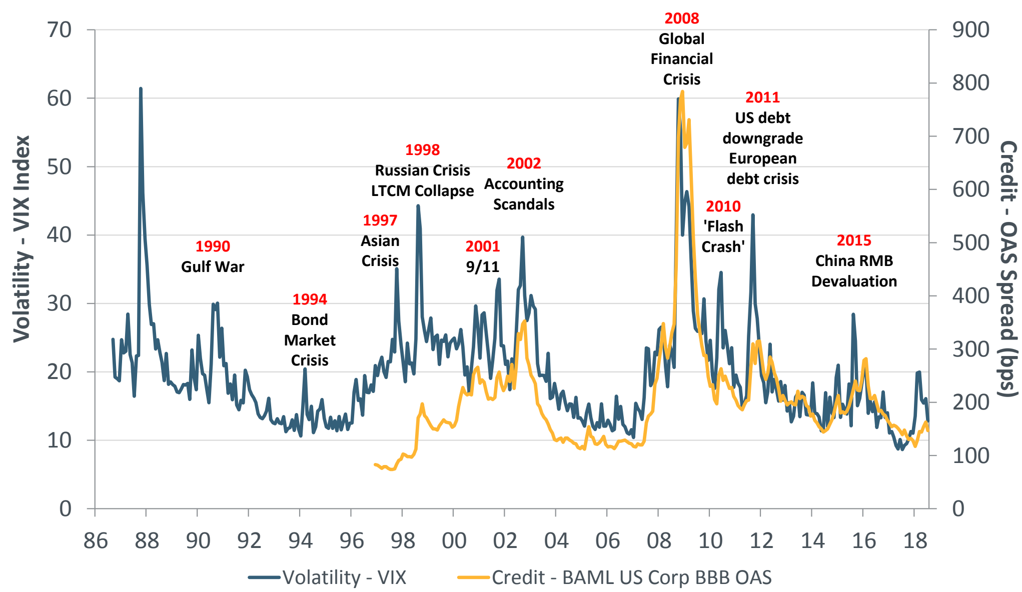
MARKET SENTIMENT PILLAR – METHODOLOGY AND SIMULATIONS

We use VIX and option-adjusted spreads (OAS) from U.S. credit markets to measure market sentiment[7]. Exhibit 12 illustrates spikes in the VIX and/or credit spreads have historically coincided with crisis periods or event driven shocks and hence can give an indication of risk-

[7] Although equivalent volatility and credit indexes exist for other geographies and could potentially be used going forward, the length of historical data is insufficient for the purposes of this study.

on / risk-off regimes. However, we do recognize that measuring the absolute levels or the relative changes in these indicators can result in fairly noisy signals which can lead to excessive turnover in a portfolio setting. To overcome these challenges, we instead compute the slope of the VIX curve (1-month / 3-month) and whether credit spreads are widening or tightening at an accelerated pace based on moving averages. The slope of the VIX curve (term structure) indicates whether the market is in a normal state (upward sloping i.e., VIX futures above spot) or in a stressed state (downward sloping, i.e., VIX futures below spot). The signal is then more homogeneous to the prevailing base levels of volatility.

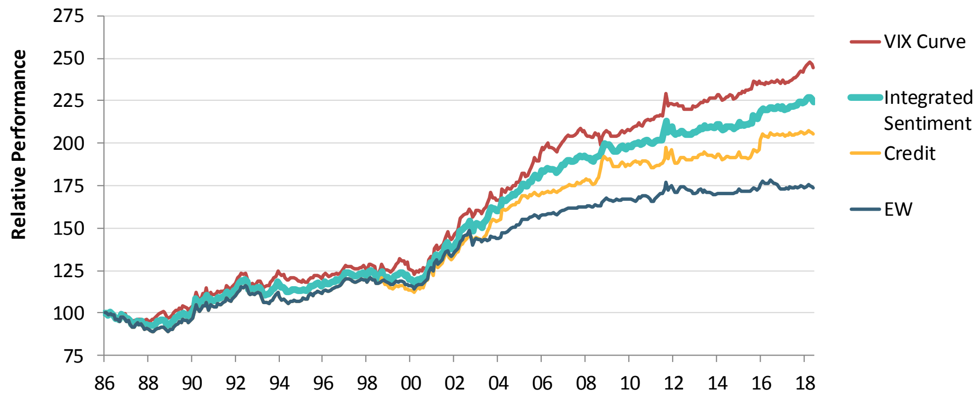
Exhibit 12: Spikes in the VIX and credit spreads during crisis periods



Sample period January 1986 – April 2017.

In a risk-on state environment, characterized by a steep upward sloping VIX curve, or prevailing credit spreads having tightened notably below their 12-month moving average, the strategy allocates to value, momentum, and low size. On the other, in a risk-off state, characterized by an inverted VIX curve, or prevailing credit spreads having tightened notably below their 12-month moving average, the strategy allocates to defensive factors, low volatility, quality and high dividend yield. If the indicators have no strong signal, the strategy has an equal-weighted allocation to all six-factor indexes.

Exhibit 13: Performance of multi-factor simulated strategies using market sentiment indicators



Metrics	MSCI World	EW	VIX Curve	Credit	Integrated Sentiment
Total Return (Ann.)	9.88%	11.65%	12.73%	12.18%	12.45%
Volatility (Ann.)	14.97%	13.77%	14.29%	13.49%	13.82%
Sharpe Ratio	0.66	0.85	0.89	0.90	0.90
Active Return (Ann.)		**1.77%**	**2.84%**	**2.30%**	**2.57%**
Active Risk (Ann.)		3.61%	4.18%	3.99%	3.83%
Information Ratio		**0.49**	**0.68**	**0.58**	**0.67**
Index Level Turnover (1-Way, Ann.)		6.9%	287%	103%	167%

Performance statistics computed in the global MSCI World Standard universe. Simulated portfolios are constructed with equal weighting of factors and monthly rebalancing. Active return and risk are computed relative to MSCI World Index. Information Ratio is defined as annualized active return/annualized active risk. Turnover is calculated as one-way average annualized turnover across all rebalancing. Sample period is January 1986 – June 2018.

In Exhibit 13 and A4, we see both the VIX curve and credit sentiment-based indicators performed well vis-à-vis the performance of an equally weighted factor portfolio. We constructed the Integrated Sentiment simulated portfolio by equally weighting simulated portfolios of volatility and credit indicators.

COMBINING THE FOUR PILLARS OF ADAPTIVE MULTI-FACTOR ALLOCATION

In the previous section, we outlined four pillars for top-down adaptive multi-factor allocation that have in isolation generated incremental returns above a simple top-down equal-weight allocation over a long historical simulation. Institutional investors may question – has there been a benefit to combine the alternative approaches? What has been the impact on performance and diversification? Our results find there was notable benefit to adopting a multi-strategy approach over the observed period. Combining different approaches has historically led to a more diversified selection of factor indexes and return sources. Exhibit 14 below shows the active return correlations amongst the strategies were low, and in some cases negative. For example, Momentum and Valuation are negatively correlated, while Market Sentiment and Macro Cycle had a weak positive correlation. The increase in diversification in a multi-strategy approach has historically led to less cyclicality relative to standalone approaches. In our results, we demonstrate the risk-adjusted returns for the combined approach were superior to the single approaches.

Exhibit 14: Correlation matrix of active returns

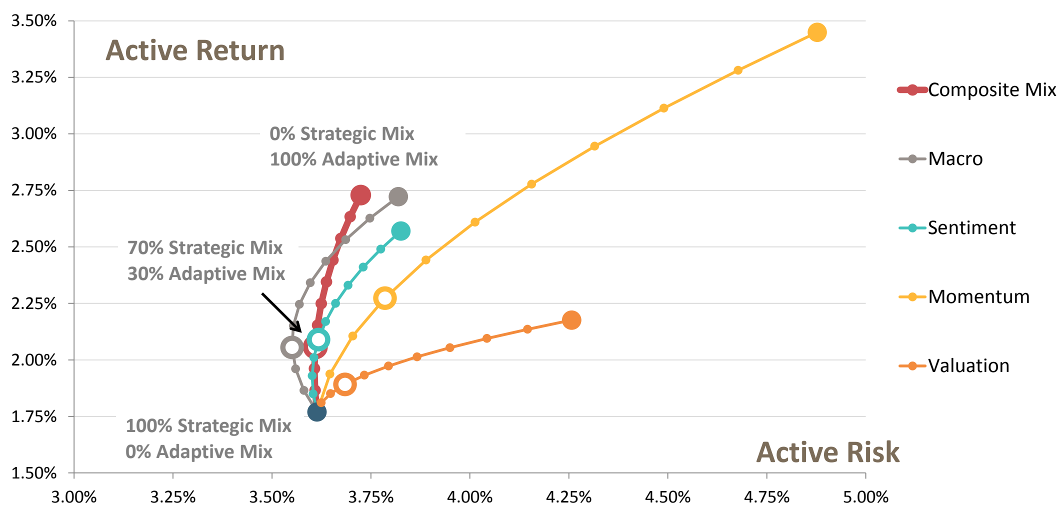
	Macro Cycle	Momentum	Valuation	Market Sentiment
Macro Cycle	1.00			
Momentum	0.32	1.00		
Valuation	-0.29	-0.40	1.00	
Market Sentiment	0.34	0.18	0.04	1.00

The table presents realized pairwise correlation of monthly active returns relative to MSCI World Index. Sample period is January 1986 – June 2018.

Is there an optimal degree of adaptation? There is a spectrum of institutional investors. On one side are strategic multi-factor investors employing a fixed dollar weight or risk weight to each factor ("Strategic Mix"). On the other side are tactical investors concentrating their positions in a subset of factors at any given time ("Adaptive Mix"). In between are other investors, perhaps with turnover or active risk constraints, tilting their exposures to capture shorter term opportunities ("Adaptive Tilt"). In Exhibit 15, we indicate performance of these three types of investors on an active risk/return plot for each adaptive multi-factor simulated strategy and a simulated composite strategy. Each dot from the 100% Strategic Mix represents an incremental 10% reallocation of capital to a simulated adaptive strategy. We have marked Adaptive Tilt, defined as a 70% Strategic Mix and 30% Adaptive Mix, on the plot. The tail end of each curve is represented by a 100% allocation to the Adaptive Mix.

In terms of performance, the 100% Strategic Mix has an active risk of 3.61% and active return of 1.77%. In comparison, the active risk and return of each pillar, represented by the Adaptive Mix, are as follows: Macro Cycle (active risk 3.82%, active return 2.72%), Momentum (active risk 4.88%, 3.45%), Valuation (active risk 4.26%, active return 2.18%), Sentiment (active risk 3.83%, active return 2.57%). The Composite Mix (active risk 3.72%, active return 2.73%), which is a combination of all four pillars, has the highest increment in returns per unit of active risk taken amongst all the individual simulated strategies considered. The (left-sided) position of the Composite Mix curve relative to the other strategies illustrates its superior efficiency, from a historical perspective.

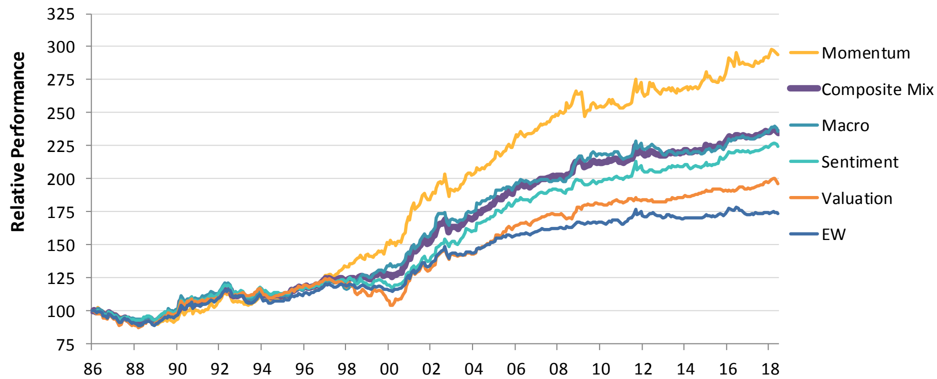
Exhibit 15: Risk-return from strategic mix to adaptive multi-factor mix across pillars



Performance statistics computed in the global MSCI World Standard universe. Adaptive Mix Portfolio is constructed with equal weighting of four pillars - Macro, Momentum, Valuation, and Sentiment, on a monthly rebalancing schedule. Active return and risk are computed relative to MSCI World Index.

Exhibit 16 summarizes, in a tabular format, performance metrics for the composite Adaptive Tilt and Adaptive Mix simulated strategies. One may question if the outperformance is concentrated during certain market environments or regimes. In Exhibit 17, we present this historical probability of outperformance relative to a top-down static multi-factor simulated strategy over a 1-year and 3-year holding period. We find all four individual pillars have a bias in outperformance, and the composite approach tends to have the highest probability of outperformance at 74% and 88% over a 1- and 3-year holding period.

Exhibit 16: Performance of multi-factor simulated strategies across single and composite pillars



Metrics	MSCI World	EW	Adaptive Tilt (70/30)	Adaptive 'Composite' Mix (0/100)
Total Return (Ann.)	9.88%	11.65%	11.94%	12.61%
Volatility (Ann.)	14.97%	13.77%	13.78%	13.84%
Sharpe Ratio	0.66	0.85	0.87	0.91
Active Return (Ann.)		**1.77%**	**2.06%**	**2.73%**
Active Risk (Ann.)		3.61%	3.61%	3.72%
Information Ratio		**0.49**	**0.57**	**0.73**
Index Level Turnover (1-Way, Ann.)		6.9%	32%	101%

Performance statistics computed in the global MSCI World Standard universe. Simulated Adaptive Mix Portfolio is constructed with equal weighting of four pillars - Macro, Momentum, Valuation, and Sentiment, on a monthly rebalancing schedule. Active return and risk are computed relative to MSCI World Index. Information Ratio is defined as annualized active return/annualized active risk. Turnover is calculated as one-way average annualized turnover across all rebalancing. Sample period is January 1986 – June 2018.

Exhibit 17: Historical probability of outperformance of simulated adaptive multi-factor strategies over a static mix

Historical Probability of Outperformance Relative to Top-down Strategic Mix					
Holding Period	Macro Cycle	Momentum	Valuation	Market Sentiment	Composite
1-year	62%	71%	60%	63%	74%
3-year	69%	83%	74%	80%	88%

Historical probabilities computed over a 1-year and 3-year holding period. Sample period is January 1986 – June 2018.

CASE STUDY: WORLD UNIVERSE – TOP-DOWN AND BOTTOM-UP IMPLEMENTATION

In the first part of this paper, based on historical data since 1986, we applied a top-down approach to both static and adaptive implementations to multi-factor allocations. Using a combination of six MSCI Factor Indexes, we found that combining factors can create diversification benefits and may have reduced turnover due to potential crossing opportunities among the individual factors. Rather than attempt to time individual factors, our adaptive portfolio maintained a multi-factor approach by imposing exposure to at least three out of the six factor indexes at any point in time.

In practice, institutional investors often evaluate bottom-up as well as top-down options to multi-factor allocations. In contrast to the top-down approach, which involves blending single factor indexes, the bottom-up approach builds a multi-factor index from stocks that are favorably exposed on average to the target factors, resulting in a significantly higher exposure through time. Readers can refer to Kulkarni et al. (2018) for a discussion that compares and contrasts top-down and bottom-up approaches to multi-factor construction.

In this section, we compare and contrast four alternative approaches to multi-factor strategies based on six factors: value, low size, momentum, quality, low volatility and yield.

1. Top-down: static (equal-weight) blend of single factor indexes
2. Top-down: adaptive blend of single factor indexes
3. Bottom-up: maximize exposure to stocks that have a high blend of static (equal-weight) target factor exposures
4. Bottom-up: maximize exposure to stocks that have a high blend of adaptive target factor exposures

For consistency and comparison purposes, we maintain the same four-pillared allocation framework for both the top-down and bottom-up adaptive approaches.[8] The main difference being that for top-down, the signals are applied to weight the factor indexes, whereas in the case of bottom-up, the signals weight the factor score at the stock level.

In terms of methodology, our bottom-up simulations apply the Barra Open Optimizer to maximize exposure to the weighted average factor scores, while maintaining a total risk profile similar to that of the benchmark at the time of rebalancing. This framework allowed us to apply other constraints to the optimization, such as target active risk, turnover, individual position weights, and active exposure to sectors, countries and other style factors.

[8] For Valuation and Momentum pillars, signals are still based on high exposure factor indexes, as a proxy for the underlying factors.

Exhibit 18 below lists the settings and constraints used in portfolio construction. The simulations used quarterly rebalancing and covered the period from November 1999 through June 2018.

Exhibit 18: Settings and constraints for long-only bottom-up multi-factor simulations

Settings & Constraints	Simulation
Benchmark	MSCI World or MSCI ACWI
Target risk	≤ Benchmark
Target tracking error	≤ 3%
Min asset weight	max (b-2%, 0%)
Max asset weight	min(benchmark+2%, b*10)
Sector exposures	+/- 5% of benchmark
Style factor exposures	+/- 0.25 of benchmark*
One-way Turnover	≤ 80% annual

*Settings and constraints for bottom-up multi-factor simulations.*In the simulation, we constrain active exposure to other style factors to be within 0.25 of the benchmark, except the factors that form basis of six standard factors , which we leave unconstrained. The constrained style factors are growth and liquidity.*

The performances of the four simulated portfolios relative to their parent index are shown in Exhibits 19 and 20. There are a number of observations. First, over the simulation period, both static equally-weighted multi-factor simulated portfolios outperformed the parent index, but the bottom-up multi-factor index delivered a higher annualized return (9.0%) than the top-down multi-factor index (7.5%). The bottom-up strategy also produced higher return/risk, Sharpe and information ratios with higher tracking error. Second, both the top-down adaptive and adaptive bottom-up multi-factor simulated portfolios added higher annualized returns (8.2% and 9.5%, respectively) than their static alternatives. Both adaptive approaches also outperformed in terms of Sharpe and information ratios, albeit they did so with higher turnover.

Exhibit 19: Performance of multi-factor simulated portfolios relative to MSCI World

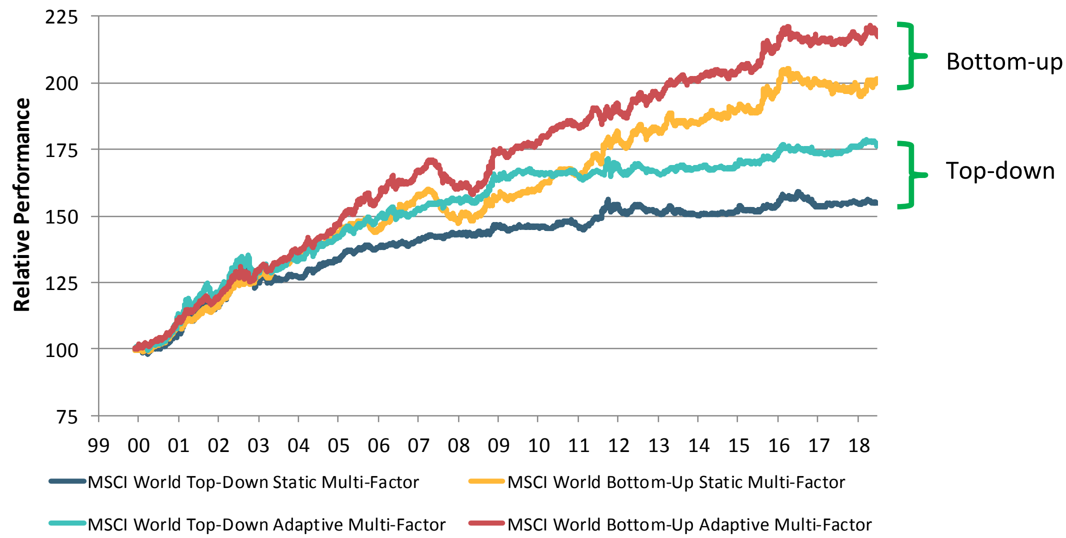


Exhibit 20: Performance of the MSCI World Index and multi-factor simulated portfolios

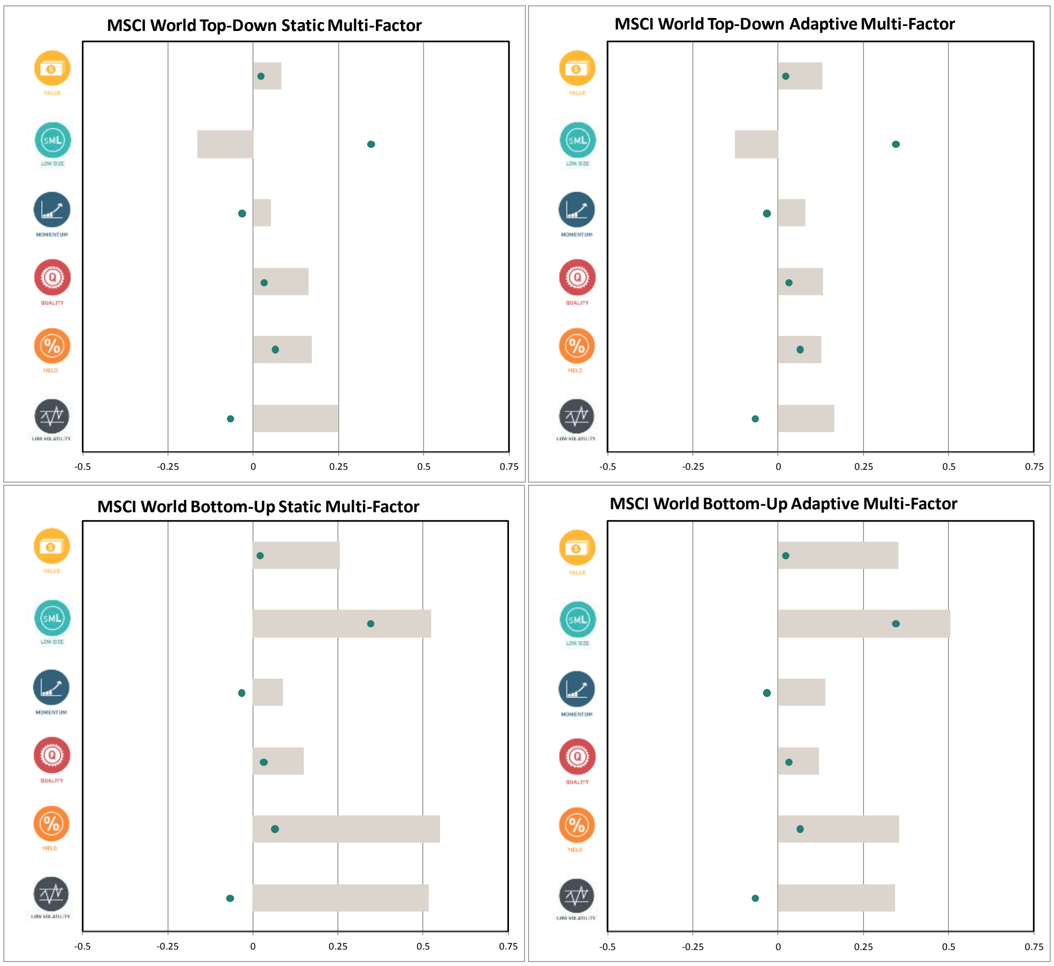
Key Metrics

	MSCI World	MSCI World Top-Down Static Multi-Factor	MSCI World Top-Down Adaptive Multi-Factor	MSCI World Bottom-Up Static Multi-Factor	MSCI World Bottom-Up Adaptive Multi-Factor
Total Return* (%)	5.0	7.5	8.2	9.0	9.5
Total Risk (%)	15.0	13.9	14.0	14.3	14.6
Return/Risk	0.33	0.54	0.59	0.63	0.65
Sharpe Ratio	0.20	0.40	0.45	0.50	0.52
Active Return (%)	0.0	2.5	3.2	4.0	4.5
Tracking Error (%)	0.0	2.9	3.1	3.0	2.9
Information Ratio	NaN	0.87	1.05	1.33	1.52
Historical Beta	1.00	0.91	0.91	0.93	0.95
No of Stocks***	1631	1621	1621	569	577
Turnover** (%)	3.8	36.1	65.4	77.1	81.0
Price To Book***	2.2	2.1	2.0	1.9	1.7
Price to Earnings***	18.4	17.4	17.3	14.9	14.5
Dividend Yield*** (%)	2.3	2.6	2.5	3.4	3.0

Key statistics of the MSCI World Index benchmark and multi-factor portfolio simulations. Turnover is annualized one-way turnover. Returns are annualized gross returns in USD. Simulation period is November 30, 1999 to June 29, 2018.

Third, the simulated adaptive multi-factor simulated portfolios had lower average valuations than static multi-factors on price-to-book, price-to-earnings and dividend yield basis (Exhibit 20). Fourth, the average Factor Classification Standard (FaCS) exposure (Bonne et al., 2018) of bottom-up portfolios is more pronounced compared to top-down portfolios (Exhibit 21). Finally, the granular average active style factor exposures of both bottom-up and top-down are similar for adaptive and static approaches, and as expected the adaptive variant displayed more time varying exposure (Exhibit 22).

Exhibit 21: Average FaCS exposures of multi-factor simulated portfolios



Statistics of FaCS exposures of various multi-factor portfolio simulations. The green dots represent average FaCS exposure of MSCI World over sample period between November 1999 and June 2018. The grey bars represent average FaCS exposure of simulated multi-factors portfolios over sample period between November 1999 and June 2018.

Exhibit 22: Active style factor exposures relative to the MSCI World Index

Statistics of style factor exposures of various multi-factor portfolio simulations. The "Current" value refers to the exposure on June 29, 2018. Note that in Bottom-up multi-factor, growth and liquidity factors were constrained between +/- .25 from benchmark.

A performance attribution provides additional insight on the contribution of the active exposures to the active risk and return of simulated multi-factor simulated portfolios. The attribution decomposes the active risk and return into components driven by currency, country, sector, styles and asset selection (Exhibit 23). We find the style return contribution is higher for both top-down adaptive (2.71%) and adaptive bottom-up (4.65%) simulated portfolios relative to their static alternatives (2.18% and 4.25%, respectively), while the risk exposures remained almost unchanged. In all simulations, the six targeted factors contributed positively to overall active return, with momentum being the major contributor.

These attribution results provided further evidence that the adaptive allocation among factors represented a separate and unique influence on the cross section of factor performances in our study.

Exhibit 23: Risk and return attribution of multi-factor portfolio simulations

	Top-Down Static Multi-Factor		Top-Down Adaptive Multi-Factor		Bottom-Up Static Multi-Factor		Bottom-Up Adaptive Multi-Factor	
	Return %	Risk %	Return %	Risk %	Return %	Risk %	Return %	Risk %
Total	7.48	13.87	8.23	14.03	9.01	14.28	9.47	14.58
Benchmark	4.99	15.05	4.99	15.05	4.99	15.05	4.99	15.05
Active	2.49	2.86	3.25	3.09	4.03	3.04	4.48	2.95
Countries	0.02	0.56	0.03	0.82	-0.04	0.55	0.18	0.48
Industries	0.24	0.83	0.32	0.9	-0.6	1.14	-0.46	1.11
Asset Selection	-0.01	0.88	0.13	1.05	0.35	1.5	0.14	1.52
Style Factors	2.18	1.97	2.71	2.01	4.25	2.1	4.65	1.97
Size	0.16	0.57	0.16	0.67	0.59	1.63	0.53	1.6
Beta	0.56	1.65	0.67	1.65	0.27	1.19	0.27	0.95
Dividend Yield	0.13	0.15	0.13	0.17	0.49	0.58	0.39	0.49
Residual Volatility	-0.02	0.11	-0.03	0.17	0.85	0.87	0.64	0.71
Earnings Quality	0.06	0.05	0.09	0.06	0.07	0.07	0.11	0.09
Mid Cap	0.05	0.18	0.07	0.23	0.25	0.65	0.25	0.64
Liquidity	0.03	0.05	-0.02	0.15	-0.11	0.28	-0.17	0.31
Long Term Reversal	0.13	0.2	0.19	0.25	0.09	0.16	0.13	0.18
Growth	-0.04	0.11	-0.03	0.11	-0.12	0.15	-0.11	0.13
Investment Quality	0.09	0.08	0.08	0.08	0.23	0.14	0.2	0.14
Earnings Variability	0.05	0.07	0.05	0.09	0.06	0.1	0.03	0.12
Leverage	0.01	0.08	0.02	0.11	0.02	0.06	0.05	0.12
Book to Price	0.09	0.15	0.23	0.21	0.39	0.3	0.56	0.41
Profitability	0.17	0.14	0.12	0.14	0.1	0.09	0.09	0.15
Momentum	0.45	0.4	0.67	0.45	0.62	0.47	1.12	0.61
Earnings Yield	0.25	0.27	0.31	0.32	0.46	0.48	0.55	0.56

CONCLUSION

In this paper, we analyzed a multi-faceted approach to dynamically allocate across factors in both developed and emerging markets using the MSCI World Index and the MSCI ACWI Index. The approach is based on four pillars: (1) Macro Cycle, (2) Momentum, (3) Valuations and (4) Market Sentiment. Through our portfolio simulations,[9] we found each pillar achieved incremental returns relative to a simple equal weighting among factors.

We found that amongst the Macro Cycle-based factor simulated strategies, the CFNAI, ADS and PMI indicators outperformed. Among Valuation-based factor simulated strategies, trailing price-to-earnings, price-to-book and price-to-cash earnings performed well. The Momentum-based factor simulated strategy using 1-month, 6-month, and 12-month historical returns outperformed with varying degrees of turnover. Market Sentiment-based factor simulated strategies using the VIX index and credit spreads performed well in both a stand-alone-basis and in an integrated framework. Moreover, the combination of the four pillars into a single simulated strategy resulted in a number of benefits. Firstly, the active return correlations amongst these approaches were low, and in some cases negative, thus bringing more diversified selection of factor indexes and return sources. Secondly, the turnover of combined approaches was lower on average than single approaches. Finally, we observed the combined approach achieved a higher degree of portfolio performance efficiency relative to each simulated strategy considered in isolation.

In the final section, we compared and contrasted four alternative approaches to multi-factor allocation – top-down static, top-down adaptive, bottom-up static, bottom-up adaptive. Over our survey period, all multi-factor simulated strategies outperformed their benchmark in terms of annualized returns, Sharpe ratios and information ratios. The adaptive multi-factor allocation simulated portfolios, in both top-down and bottom-up approaches, generated an active return of 3.25% and 4.48% respectively, while the top-down static and bottom-up approaches delivered 2.49% and 4.03%.

While the adaptive multi-factor simulated strategies outperformed static approaches in our study, the conclusions could vary depending on the starting universe and/or the selection of factors. Moreover, it’s possible there may not be any outperformance in alternative cases.

[9] Since 1986 for the MSCI World Index and since January 1999 for the MSCI ACWI Index

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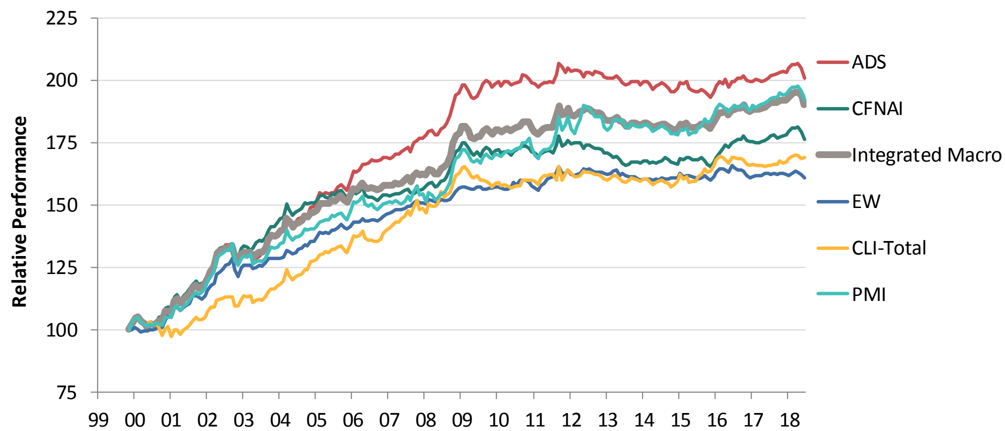
APPENDIX

In this section, we display performance of multi-factor simulated portfolios based on MSCI ACWI using individual pillars as well as an equal weighted combination of four pillars in long-only portfolio construction setting. We include simulation results of both top-down and bottom-up implementations.

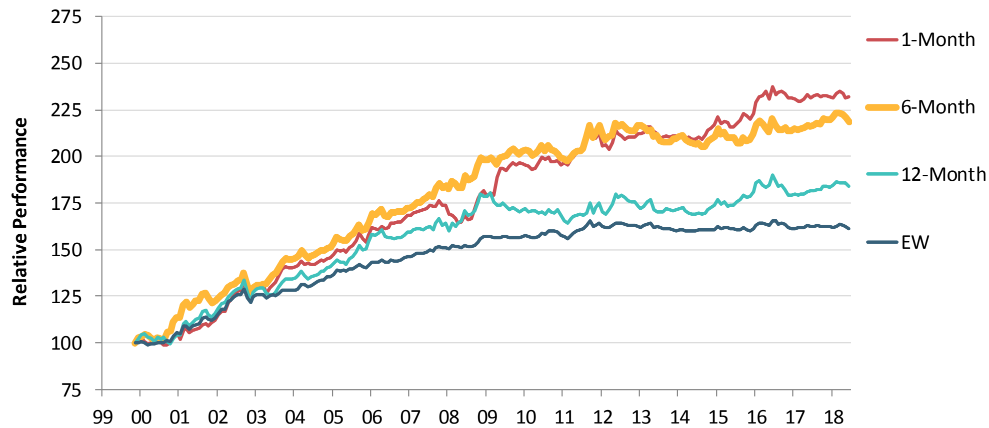
Exhibit A1: Performance relative to MSCI ACWI of multi-factor simulated strategies using macro cycle based indicators



Metrics	MSCI ACWI	EW	ADS	CFNAI	PMI	CLI-Total	Integrated Macro
Total Return (Ann.)	6.27%	8.88%	10.18%	9.40%	9.97%	9.27%	9.85%
Volatility (Ann.)	15.39%	14.35%	14.74%	14.65%	14.31%	14.93%	14.48%
Sharpe Ratio	0.41	0.62	0.69	0.64	0.70	0.62	0.68
Active Return (Ann.)		**2.61%**	**3.91%**	**3.12%**	**3.70%**	**2.99%**	**3.58%**
Active Risk (Ann.)		2.90%	3.61%	3.46%	4.38%	3.99%	3.51%
Information Ratio		**0.90**	**1.08**	**0.90**	**0.84**	**0.75**	**1.02**
Index Level Turnover (1-Way, Ann.)		6.9%	204%	160%	112%	67%	148%

Performance statistics computed in the global MSCI ACWI Standard universe. Simulated portfolios are constructed with equal weighting of factors and monthly rebalancing. Active return and risk are computed relative to MSCI ACWI. Information Ratio is defined as annualized active return/annualized active risk. Turnover is calculated as one-way average annualized turnover across all rebalancing. Sample period is November 1999 – June 2018.

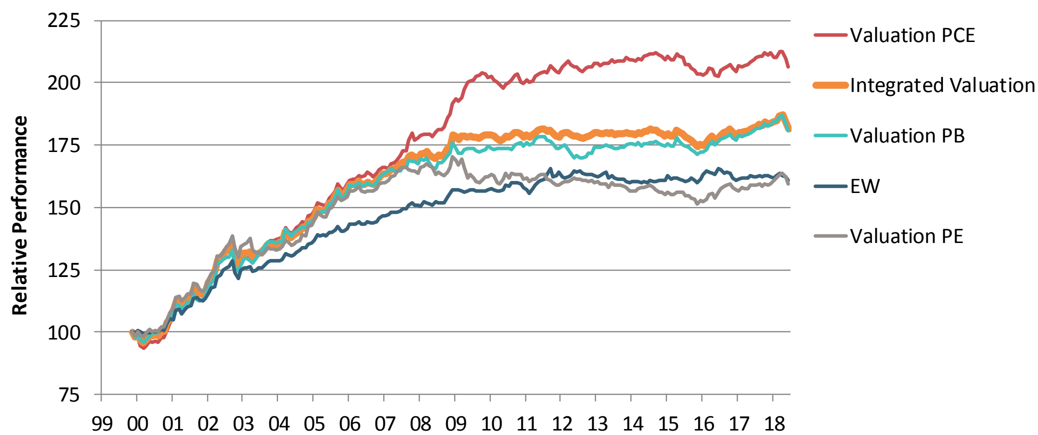
Exhibit A2: Performance relative to MSCI ACWI of multi-factor simulated strategies using momentum based indicators



Metrics	MSCI ACWI	EW	1-Month	6-Month	12-Month
Total Return (Ann.)	6.27%	8.88%	10.93%	10.69%	9.77%
Volatility (Ann.)	15.39%	14.35%	14.47%	14.23%	14.27%
Sharpe Ratio	0.41	0.62	0.76	0.75	0.68
Active Return (Ann.)		**2.61%**	**4.66%**	**4.41%**	**3.49%**
Active Risk (Ann.)		2.90%	4.79%	4.80%	4.95%
Information Ratio		**0.90**	**0.97**	**0.92**	**0.71**
Index Level Turnover (1-Way, Ann.)		6.9%	550%	199%	170%

Performance statistics computed in the global MSCI ACWI Standard universe. Simulated portfolios are constructed with equal weighting of factors and monthly rebalancing. Active return and risk are computed relative to MSCI ACWI. Information Ratio is defined as annualized active return/annualized active risk. Turnover is calculated as one-way average annualized turnover across all rebalancing. Sample period is November 1999 – June 2018.

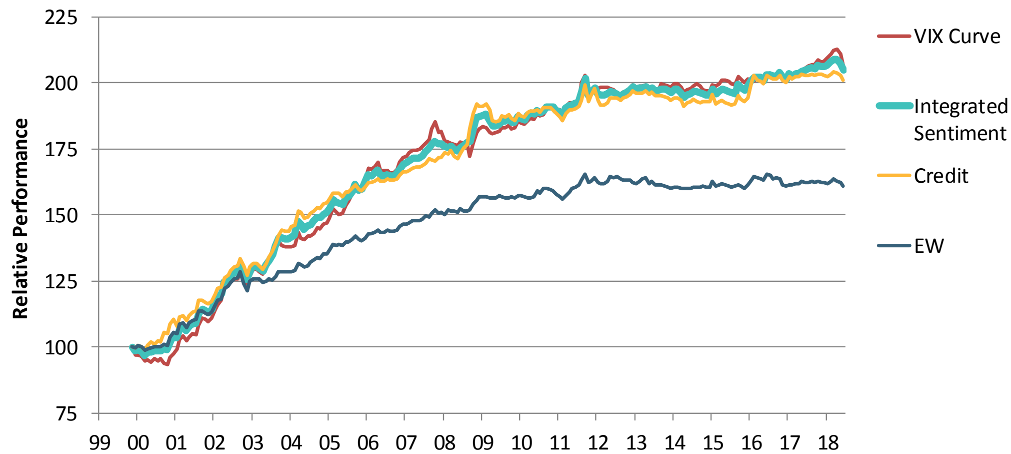
Exhibit A3: Performance relative to MSCI ACWI of multi-factor simulated strategies using valuation based indicators



Metrics	MSCI ACWI	EW	Valuation (P/E)	Valuation (P/CE)	Valuation (P/B)	Integrated Valuation
Total Return (Ann.)	6.27%	8.88%	8.78%	10.21%	9.51%	9.50%
Volatility (Ann.)	15.39%	14.35%	14.53%	15.18%	15.40%	14.96%
Sharpe Ratio	0.41	0.62	0.60	0.67	0.62	0.64
Active Return (Ann.)		**2.61%**	**2.51%**	**3.94%**	**3.24%**	**3.23%**
Active Risk (Ann.)		2.90%	3.94%	3.77%	3.76%	3.51%
Information Ratio		**0.90**	**0.64**	**1.05**	**0.86**	**0.92**
Index Level Turnover (1-Way, Ann.)		6.9%	163%	90%	82%	102%

Performance statistics computed in the global MSCI ACWI Standard universe. Simulated portfolios are constructed with equal weighting of factors and monthly rebalancing. Active return and risk are computed relative to MSCI ACWI. Information Ratio is defined as annualized active return/annualized active risk. Turnover is calculated as one-way average annualized turnover across all rebalancing. Sample period is November 1999 – June 2018.

Exhibit A4: Performance relative to MSCI ACWI of multi-factor simulated strategies using mark sentiment based indicators



Metrics	MSCI ACWI	EW	VIX Curve	Credit	Integrated Sentiment
Total Return (Ann.)	6.27%	8.88%	10.36%	10.11%	10.23%
Volatility (Ann.)	15.39%	14.35%	15.24%	13.72%	14.38%
Sharpe Ratio	0.41	0.62	0.68	0.74	0.71
Active Return (Ann.)		**2.61%**	**4.08%**	**3.84%**	**3.96%**
Active Risk (Ann.)		2.90%	4.07%	3.83%	3.48%
Information Ratio		**0.90**	**1.00**	**1.00**	**1.14**
Index Level Turnover (1-Way, Ann.)		6.9%	263%	108%	168%

Performance statistics computed in the global MSCI ACWI Standard universe. Simulated portfolios are constructed with equal weighting of factors and monthly rebalancing. Active return and risk are computed relative to MSCI ACWI. Information Ratio is defined as annualized active return/annualized active risk. Turnover is calculated as one-way average annualized turnover across all rebalancing. Sample period is November 1999 – June 2018.

Exhibit A5: Performance relative to MSCI ACWI of long-only multi factors simulated portfolios relative to benchmark

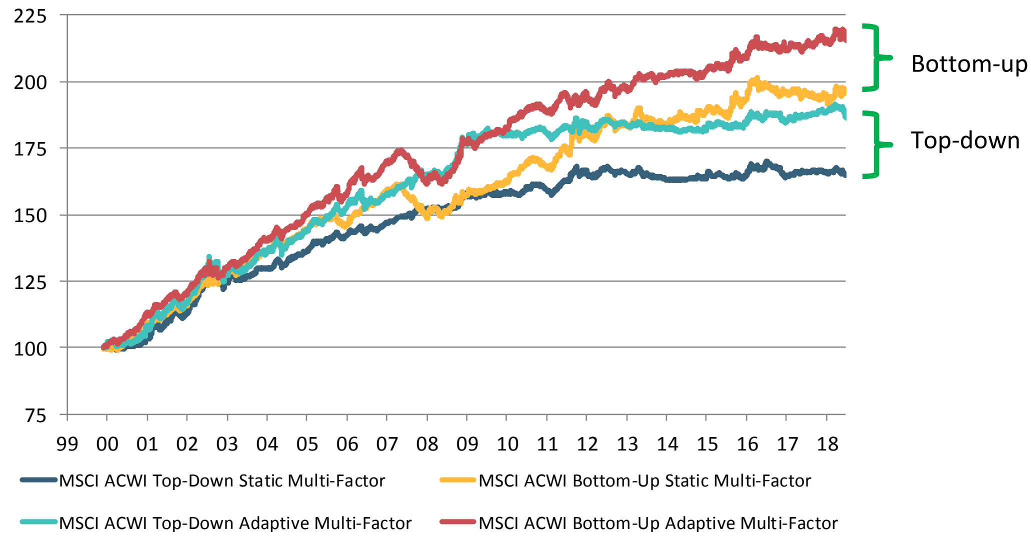


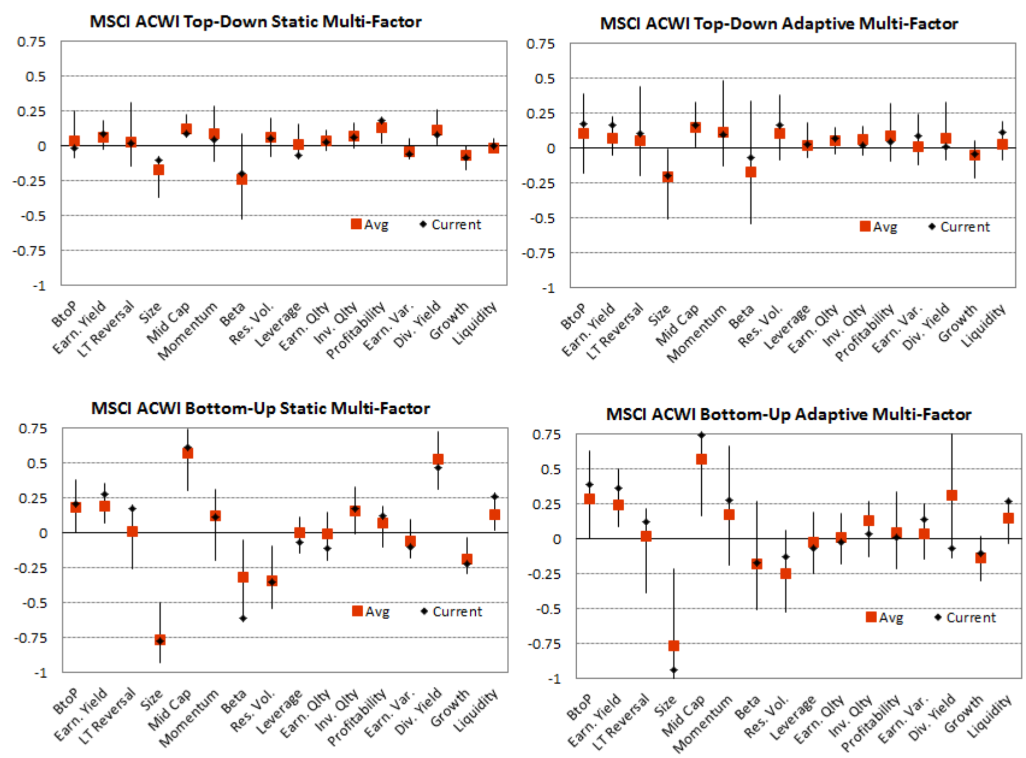
Exhibit A6: Performance of MSCI ACWI and multi-factor simulated portfolios

Key Metrics

	MSCI ACWI	MSCI ACWI Top-Down Static Multi-Factor	MSCI ACWI Top-Down Adaptive Multi-Factor	MSCI ACWI Bottom-Up Static Multi-Factor	MSCI ACWI Bottom-Up Adaptive Multi-Factor
Total Return* (%)	5.0	7.9	8.6	8.9	9.5
Total Risk (%)	15.4	14.4	14.6	14.7	14.9
Return/Risk	0.33	0.55	0.59	0.61	0.63
Sharpe Ratio	0.20	0.41	0.46	0.48	0.51
Active Return (%)	0.0	2.9	3.6	3.9	4.4
Tracking Error (%)	0.0	2.9	3.2	3.0	2.8
Information Ratio	NaN	1.00	1.11	1.32	1.56
Historical Beta	1.00	0.92	0.93	0.93	0.95
No of Stocks***	2427	2423	2423	797	832
Turnover** (%)	4.2	36.2	65.9	76.7	80.7
Price To Book***	2.2	2.0	1.8	1.8	1.6
Price to Earnings***	18.0	16.8	16.8	14.2	14.0
Dividend Yield*** (%)	2.3	2.6	2.6	3.5	3.1

Key statistics of the MSCI ACWI Index and multi-factor portfolio simulations. Turnover is annualized one-way turnover. Returns are annualized gross returns in USD. Simulation period is November 30, 1999 to June 29, 2018.

Exhibit A7: Active style factor exposures relative to MSCI ACWI



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