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In a 2003 speech before the NMS Endowments and Foundations Conference, Peter Bernstein suggested that adherence to a fixed and undiversified policy portfolio is dangerous. His warning was largely ignored. A year later, Arnott [2004] showed that the 20 largest U.S. corporate pension funds were willing to accept 12% annual volatility in total return and 15% tracking error relative to liabilities, but only 2.5% tracking error relative to peers. Put another way, avoidance of risk relative to peers was five times as important to pension sponsors as avoidance of asset volatility and six times as important as managing the volatility of the true economic pension funding ratio (absent actuarial smoothing).

Policy portfolios and benchmarks are as dominant today as they were 15 years ago and roughly as anchored to peer group norms now as then. Over the last decade and a half, we have experienced the highs of euphoric bubbles as well as a global panic of epic proportions. How can it be that holding the same asset mix is equally prudent for funds with radically different funding ratios and investment horizons under such divergent market conditions? Though we have seen growing use of a broader toolkit of diversifying asset classes, reliance on the omnipresent 60/40 domestic stock/bond portfolio remains at the core of many investors' holdings.

Diversification adds tremendous value,[1] and asset owners are increasingly demanding that their managers take greater advantage of diversification opportunities. To do so, asset allocators need to better understand what is necessary for well-researched and robust asset-return drivers, typically studied in a long/short context, to work in their unlevered long-only portfolios.

In this article, we apply the considerable body of research on predictable asset class returns to the task of managing an unlevered long-only multi-asset portfolio and show that a broad investment opportunity set, which reflects the desire to be, on average, very diversified, is a powerful source of incremental return. As we translate lightly correlated sources of excess returns from the long/short space common in academia to a long-only unlevered portfolio, we hope that investors will hear our plea: Please embrace broader diversification in your quest for long-term investment success.[2]

OUR APPROACH

A rich body of work, going back decades, supports the predictability of returns within an asset class such as equities. Campbell and Shiller [1988], Fama and French [1989], and Cochrane [2007] conclude that the expected returns are time varying in the cross section of equities and that higher yields (carry) and lower valuations (value) are associated with higher future returns. Carry has been documented as a return driver by Ahmerkamp and Grant [2013], Koijen et al. [2016], and most recently, Baltas [2017, forthcoming]. Momentum has been extensively investigated both across time and across assets, with Jegadeesh and Titman [1993] and Moskowitz et al. [2012] presenting well-known studies on the predictability of future returns based on recent strong performance.

In contrast, the literature has only recently begun to investigate the combination of value and momentum signals across asset classes in a levered long/short multi-asset setting.[3] The results to date are promising because the return-generating mechanisms associated with carry, value, and momentum are distinct and lightly correlated for most asset classes, thus making for attractive combinations. For instance, whereas the return signals of a value strategy are long lived and rely in part on mean reversion to a long-term valuation norm, momentum signals are very short lived and require the continuation of differential return or movement away from the mean return; they are typically negatively correlated. The carry and value signals, which are closely related in equities, behave very differently in fixed income, currencies, and commodities; in these asset classes, carry portfolios often move counter to value portfolios.

We go beyond the existing literature by considering the usefulness of carry, value, and momentum in unlevered global tactical asset allocation (GTAA) strategies. Our approach is a simpler test than many in academia, but it has far more practical import relative to the long/short levered portfolios studied in the literature. The tests we undertake reflect the constraints that are typical in real-world applications, using asset classes often found in multi-asset class portfolios.

We conduct our analysis over the 37-year period from 1980 through 2016, constructing three multi-asset class universes: 1) a narrowly focused 2-asset U.S. universe, 2) a 4-asset global universe, and 3) a 15-asset class diversified universe.[4] Our main finding is that an investor with a risk budget of about 2% (consistent with the findings of Arnott [2004] on peer group active risk tolerance) could have added economically significant returns in an unlevered portfolio, *as long as the opportunity set of asset classes was broad enough*, by relying on the three return drivers we study: carry, value, and momentum. When these three return drivers are put to work in the diversified universe of 15 asset classes, the annualized risk-adjusted alpha is 122 basis points (bps) and tracking error is 184 bps, for an active information ratio of 0.67.[5] In the more-restricted U.S. and Global Universes, the annualized risk-adjusted alpha opportunity is reduced, producing information ratios of 0.13 and 0.18, respectively.

To be sure, many domestic tactical asset allocation (TAA) strategies—including our own—have fared much better than this over much of our 37-year test period. We deliberately choose hypersimple models to mitigate any avoidable risk of look-ahead bias and data mining. Over the time span of our analysis, much of which has been characterized by a relentless bull market in both stocks and bonds, hypersimple TAA models have been surprisingly weak in the basic domestic stock–bond context. We observe that additional asset classes increase the efficacy of TAA by a far greater margin than most observers would likely expect. In contrast to the broad universe, the more-restricted universes have not produced statistically significant adjusted alphas over a protracted time horizon.

Readers may be tempted to criticize this study as unduly simple, even simplistic. *That's our point!* Even hypersimple models, which sharply mitigate the risk of data mining in historical simulation, show surprisingly robust results, with value-add that rises almost linearly with the number of asset classes we include in our tactical program. These results should raise the confidence of the asset allocation community that it is possible to successfully apply transparent factor-based return methods to global asset classes, even for investors operating in the unlevered long-only space. Would more sophisticated models work better? If well crafted, of course they could. But that is not the point of our research. Our point is that broader diversification has startling benefits, enhancing the efficacy of TAA strategies, as long as the portfolio embraces a broad opportunity set with a wide array of diversifying markets.

How does all of this relate to benchmarks? As we move from simple (U.S. stocks and bonds) to diversified (15 asset classes), our investment guidelines must first *permit* the additional asset classes. If we do not allow the additional asset classes, we cannot earn excess returns from tactically favoring or shunning these markets. To extract further benefit, we must also allow symmetric bets, both for and against these markets, which means that the policy portfolio or benchmark must include these asset classes. If we do not include the additional asset classes in our benchmark, we can only add value by

EXHIBIT 1

Summary of Asset Class Indexes

Asset Class[a,b]	Asset Type	Index Name	Return over RFR	Volatility	Sharpe Ratio	Data Availability[c]
BarCap Agg*,**	Fixed Income	Barclays U.S. Aggregate (Unhedged)	3.25%	5.32%	0.61	1/31/1975
U.S. Equities*,**	Equities	S&P 500	7.68%	15.05%	0.51	1/31/1975
Global Agg Ex-U.S.**	Global Bonds	Barclays Global Agg Ex-U.S. (Unhedged)	2.92%	8.36%	0.35	2/28/1990
Developed Ex-U.S. Equities**	Equities	MSCI EAFE	5.79%	17.33%	0.33	1/31/1975
Interm Credit	Credit	Barclays U.S. Interm Credit (Unhedged)	3.40%	4.88%	0.70	1/31/1975
Commodities	Real Return	S&P GSCI Commodity Index	0.92%	19.56%	0.05	1/31/1975
Interm Treasuries	Fixed Income	Barclays U.S. Treasury Intermediate (Unhedged)	2.43%	3.97%	0.61	1/31/1975
U.S. TIPS	Real Return	Barclays U.S. Treasury U.S. TIPS (Unhedged)	3.41%	5.66%	0.60	4/30/1997
High Yield	Credit	Barclays Corporate High Yield (Unhedged)	5.39%	8.46%	0.64	8/31/1983
EM Local Currency	Global Bonds	JP Morgan ELMI+ Composite (Unhedged)	3.02%	7.29%	0.41	1/31/1994
Long Treasuries	Fixed Income	Barclays U.S. Treasury Long (Unhedged)	4.92%	11.15%	0.44	1/31/1975
EM Bonds	Global Bonds	JP Morgan EMBI+ (Unhedged)	7.29%	13.26%	0.55	1/31/1994
Leveraged Loans	Credit	JPM Leveraged Loan Index	3.36%	5.69%	0.59	1/31/1992
REITs	Real Return	FTSE NAREIT All REITs	7.33%	16.68%	0.44	1/31/1975
EM Equities	Equities	MSCI EM	9.59%	23.06%	0.42	1/31/1988

*Notes: Returns, volatilities, and Sharpe ratios are measured over the backtest period from January 1980 through December 2016. [a]All asset classes belong to the diversified universe; * denotes as belonging to the U.S. universe; ** denotes as belonging to the global universe. [b]Barclays U.S. Aggregate Jan 1976–Dec 2016 back-spliced with Ibbotson Associates Intermediate-Term Govt Jan 1975–Dec 1976; Barclays U.S. Treasury Long Jan 1992–Dec 2016 back-spliced with Ibbotson Associates U.S. Long-Term Govt from Jan 1975–Dec 1992; JP Morgan Leveraged Loan Index Jan 2007–Dec 2016 back-spliced with Credit Suisse Leveraged Loan Index, Jan 1992–Dec 2007. [c]The carry model is available from this date; the value model is available five years after this date; and the momentum model is available one year after.*

Source: Research Affiliates, LLC, using data from Bloomberg, Robert Shiller's Online Data, Moody's, and REIT.com.

betting against our benchmark asset classes and in favor of the diversifying markets.

For the simple exercise we undertake here, we use equal weighting, purely for illustrative purposes. We find that surprisingly simple models can add surprisingly large excess returns with surprisingly modest asset allocation "bets" when applied across a sufficiently diverse array of asset classes. We can only extract this benefit if we are willing to revisit—in a material way—our policy portfolio, our investment guidelines, and our benchmark.

THE DATA

Our dataset encompasses a broad array of asset classes including fixed income, commodities, real estate investment trusts (REITs), and equity investments, as listed in Exhibit 1. Our source asset class return and yield data are from Bloomberg. Our U.S. equity earnings data are from Robert Shiller; corporate default and recovery rates are from Moody's; and dividend data for REITs are from REIT.com. The inception date for our strategy portfolios is year-end 1979. Therefore, our analysis begins on January 1, 1980, and extends through December 31, 2016.

THE MODEL

Carry, value, and momentum are among the most thoroughly studied return factors within the academic community. Early research focused on within-asset class applicability of return drivers, resulting in a dearth of research on the application of these strategies across asset classes. Although researchers have made up for this lack of attention in recent years, the application of these ideas has focused on broad universes that are not the asset classes typically used in traditional investor portfolios. Thus, the question remains as to how these return drivers apply to the unlevered long-only multi-asset class framework, the prevailing investment construct under which most investment assets are managed.

We briefly summarize the logic of the three return drivers we study.

Carry. Carry is the expected return of an asset class under the assumption that its valuation will remain constant. We build on the definition for carry outlined by Koijen et al. [2016] as a model-free estimate of return without changes in price. In our application, however, we include expected price changes such as, but not limited to, growth in earnings for equities and expected defaults or downgrades for credit investments. Though we can ignore these components when comparing securities within an asset class, the expected price appreciation or loss is essential when comparing across assets in the context of our multi-asset class portfolios.

Because yields are often not directly comparable across asset classes, we use the following measures for carry. We deliberately choose very simple measures in order to minimize the impact of data mining and look-ahead bias. These are the same measures an investor might reasonably have chosen a quarter- or even half-century ago.

For fixed-income markets, we use the current nominal yield of the relevant index, adjusting credit assets by a negative growth rate proportional to the inception-to-date average downgrades and defaults calculated from the Moody's annual default table for speculative-grade bonds, going back to 1920. For global and emerging market bonds, we assume the same average downgrades and default rates as the corresponding credit ratings of U.S. corporate bonds.

For collateralized commodities, we proxy the yield of the S&P GSCI Commodity Index by the one-year forward roll yield, as it is commonly called in the commodity trading community, which we calculate as the trailing five-year total return minus the spot return of the index. To this real yield we add trailing three-year inflation, as a proxy for the expected rate of inflation, and the nominal T-bill rate, as the carry earned on the commodity index's collateral.

For REITs, we use the current dividend yield of the FTSE NAREIT All REITs Index adjusted by the inception-to-date average real dividend per share growth and the trailing three-year inflation rate.

Finally, for equities, we use the current dividend yield of the relevant index and a nominal growth rate. We define the nominal growth rate as the sum of the annualized inception-to-date real U.S. earnings growth from Robert Shiller's Online Data and the trailing three-year inflation rate.

Value. In contrast to carry, value does not assume that current valuations will prevail. Value assumes that prices will revert toward historical normalized valuation averages—an assumption consistent with literature focused on mean reversion. In the equity space, Fama and French [1996] and, more recently, Gerakos and Linnainmaa [2016] show that the use of reversion to a historical norm for a valuation metric, such as price-to-book ratio, is substantially equivalent to the use of the negative of a security's five-year price return. Therefore, consistent with our preference for simplicity over complexity, our value indicator is the negative of the annualized five-year total return for each of our asset classes. Although it would have been easy to construct a more sophisticated and more powerful measure tailored to each asset class, that would introduce an element of look-ahead bias and data mining because it would incorporate the learnings of recent decades. The naive metric we use is surprisingly powerful.

Momentum. Momentum—the continuation of stock prices moving higher or lower—is well documented across geographies, asset classes, and time periods. A common explanation for why the momentum premium exists is that investors initially underreact to surprises (e.g., earnings announcements for stocks), and the news is not immediately incorporated into an asset's price but is reflected later. Thus, for periods of up to about a year after the news is announced, investors will tend to bid the price of an asset up on what appears to be good news, or vice versa. As such, our momentum indicator for each asset is simply its trailing one-year return. We do not use standard momentum—defined as trailing one-year return, excluding the latest month—because it was first explored in the literature *after* the start of our test period. Again, we are aggressively seeking to avoid data mining and look-ahead bias, insofar as that is possible in a backtest.

As is typical in academic backtests, momentum-built portfolios perform well (although not over the last quarter-century, as noted by Arnott et al. [2017], who show that standard momentum has lost money from its 1999 peak through 2016), but a few caveats are worth noting. First, these portfolios derive most of their outperformance during good times. Missing the turn when the trend reverses can lead to substantial drawdowns. Second, implementing momentum as a stand-alone strategy requires substantial and time-sensitive trading that can meaningfully erode returns. If trading costs are more than minimal, the alpha of momentum strategies can easily disappear, especially if these strategies are used on a stand-alone basis.

In summary, for each asset class we build the following three signals, which we use in the construction of our TAA strategy portfolios:

- **Carry** = *yield* + *growth; growth is specific to each asset class.*
- **Value** = *negative of the trailing five-year annualized return.*
- **Momentum** = *trailing one-year return.*

PORTFOLIO CONSTRUCTION

We consider carry, value, and momentum strategy portfolios based on three universes of increasing breadth. The U.S. universe consists of two asset classes: U.S. stocks and bonds, both cap-weighted. The global universe consists of four asset classes: U.S. and developed ex-U.S. stocks and bonds. The diversified universe includes the 15 asset classes listed in Exhibit 1, but only for the years when data for each were available. For example, by March 1990, the universe included 11 asset classes for which data were available. After January 1992, the number of asset classes rose to 12 when data for leveraged loans became available; after January 1994, emerging market bonds and emerging market currencies were added; and after April 1997, the fifteenth asset class, U.S. TIPS, entered the diversified universe when data for the asset class first became available.

The benchmark for each portfolio strategy we consider is the equal-weighted, $\frac{1}{N}$, portfolio. DeMiguel et al. [2009] show that the equal-weighted strategy is a rather robust and well-performing portfolio that is surprisingly difficult to better with any out-of-sample strategy. In our analysis, we apply a heuristic-based approach to constructing the carry, value, and momentum strategy portfolios. For a given signal each month, we rank-order the cross section of asset classes and calculate percentile scores for each asset class in the opportunity set. For a given threshold θ (set to 50% for the main results), we build an active-weight portfolio relative to the $\frac{1}{N}$ benchmark by overweighting the asset classes with percentile scores higher than θ, and underweighting those lower than $1 - \theta$. The aggregate of the overweight investments and the aggregate of the underweight investments are each given equal representation, ensuring that the portfolio balances.

Because the number of assets composing each universe is different, the neutral position in each asset varies. For example, the restrictive U.S. universe holds two assets at $\frac{1}{2} = 50\%$, while the diversified universe holds 15 assets, each at $\frac{1}{15} = 6.67\%$. Because we have a no-leverage restriction, the weight of an asset in a universe $\frac{1}{N}$ would limit the active underweight in that asset class for a particular universe. In order to have similar tracking errors for the various implementations, we limit the underweight positions for universes with less than eight assets to $\frac{1}{2N}$. This approach delivers similar tracking errors of about 2% a year for the different universes. Thus, the active weights for the asset classes are

$$w = \pm \begin{cases} \frac{1}{2N} & \text{for } N < 8 \\ \frac{1}{N} & \text{for } N \geq 8 \end{cases} \tag{1}$$

We do not exclude strategies that empirically failed over our test period, both to avoid unnecessary data mining and to avoid performance chasing. That said, we recognize that varying allocations across the strategies, based on when one is more likely to outperform the other, may lead to improved results. For example, cross-sectional stock return predictability seems to concentrate in bad times (see Tetlock [2007], Patton and Timmermann [2010], and Cujean and Hasler [2015]). Alternatively, momentum primarily extracts positive performance during strong market conditions and is plagued by substantial drawdowns—often described as momentum crashes—in less favorable environments, especially during and just after bear-market lows (see Daniel and Moskowitz [2016]).

A strategy often captures, in aggregate, various market risks that are simply average market exposure

Exhibit 2

Strategy Performance and Turnover by Averaging Period (diversified universe), January 1980–December 2016

	Carry			Value			Momentum		
	Alpha Return	Turnover	Alpha per Turnover	Alpha Return	Turnover	Alpha per Turnover	Alpha Return	Turnover	Alpha per Turnover
1 m	−0.42%	55%	−0.76%	0.89%	75%	1.19%	1.59%	148%	1.08%
3 m	0.51%	40%	1.28%	0.87%	49%	1.79%	1.06%	88%	1.21%
6 m	0.69%	32%	2.13%	1.17%	39%	2.97%	0.18%	66%	0.27%
9 m	0.77%	28%	2.71%	1.30%	34%	3.82%	0.01%	55%	0.02%
12 m	0.77%	26%	2.96%	1.32%	31%	4.28%	−0.23%	49%	−0.47%
18 m	0.84%	23%	3.71%	1.39%	26%	5.26%	−0.59%	38%	−1.56%
24 m	0.79%	20%	3.86%	1.35%	23%	5.79%	−0.67%	30%	−2.23%

Notes: Calculated monthly over the test period. All figures are annualized.

Source: Research Affiliates, LLC, using data from Bloomberg, Robert Shiller's Online Data, Moody's, and REIT.com.

and should not be considered alpha. We could adjust the signals on an ad hoc basis to create strategies that are more market neutral, but this requires substantial knowledge of the dataset averages. It would be very difficult to introduce any such adjustments without inadvertently introducing look-ahead bias. Our preferred approach is to calculate a measure of risk-adjusted alpha that is in excess of average market risk exposures.

To calculate our risk-adjusted alpha, we follow the approach of Ilmanen and Kizer [2012] and calculate the residual return based on a six-market-factor model, including four factors from the online Kenneth French Data Library—market beta (RMRF), value (HML), size (SMB), and momentum (MOM)—and two bond factors derived from our dataset: the return of long-term Treasuries minus one-month Treasury-bills (TERM), and the return of long-term corporate bonds minus long-term Treasuries (DEF).[6] We report the intercept of the factor regressions as risk-adjusted alpha or in tables as just alpha.

We undertake an additional step in strategy construction. To generate more-realistic investment strategies, we allow for the time averaging of portfolios, which can be thought of as monthly partial rebalancing, although it's not quite the same. For the carry and value strategies, the portfolio's monthly weight is the average of the prior 12 months' model weights, implying that a portfolio is held for 12 months rather than rebalanced monthly. We do this for two reasons:

1. Both carry and value are longer-term strategies and require longer holding periods to harvest returns from the return drivers.
2. Longer holding periods meaningfully decrease the required trading and related trading costs of the portfolios.

In contrast, longer holding periods, even after considering the reduction in turnover and related costs, decay the return potential of a momentum strategy.

Exhibit 2 shows how various averaging periods affect the alpha and turnover of each strategy in the diversified universe. As expected, alpha increases in both the carry and value strategies as the time horizon of averaging extends to 12–18 months. Also consistent with expectations, the momentum strategy shows monotonically declining alpha from the first month onward and declining alpha per unit of turnover from a three-month horizon onward.

MAIN RESULTS

Over a span of 37 years—from the start of 1980 through the end of 2016—the majority of the individual strategies we study earned positive alphas, many of which are statistically significant, across the three universes. The most striking results were for the diversified universe, in which most of the individual strategies provided statistically significant alphas at a 5% threshold, and all strategy combinations had statistically significant alphas at a 1% threshold. Exhibit 3 presents the return, risk, and turnover characteristics of the individual, pair, and combination (all three) strategies for each of the three universes in our study.

Exhibit 3

Strategy Performance by Universe, January 1980–December 2016

	Alpha Return	Tracking Error	Info Ratio	*t*-Value	Turnover
U.S. Universe					
Carry	−0.32%	3.06%	−0.10	−0.60	15%
Value	0.76%	2.76%	0.28	1.59	15%
Momentum	0.24%	3.32%	0.07	0.43	73%
Carry & Value	0.22%	2.40%	0.09	0.53	15%
Carry & Mom	−0.04%	1.98%	−0.02	−0.11	43%
Value & Mom	0.50%	2.15%	0.23	1.35	43%
Combination	0.23%	1.80%	0.13	0.73	33%
Global Universe					
Carry	−0.36%	2.14%	–0.17	−0.98	15%
Value	0.85%*	2.54%	0.34	1.94	19%
Momentum	0.47%	2.99%	0.16	0.90	67%
Carry & Value	0.25%	1.92%	0.13	0.74	16%
Carry & Mom	0.05%	1.82%	0.03	0.17	39%
Value & Mom	0.66%*	2.19%	0.30	1.74	41%
Combination	0.32%	1.74%	0.18	1.06	31%
Diversified Universe					
Carry	0.77%*	2.59%	0.30	1.72	26%
Value	1.32%**	3.34%	0.39	2.27	31%
Momentum	1.59%**	4.01%	0.40	2.28	148%
Carry & Value	1.04%***	2.14%	0.49	2.82	26%
Carry & Mom	1.18%***	2.36%	0.50	2.88	84%
Value & Mom	1.45%***	2.44%	0.60	3.43	86%
Combination	1.22%***	1.84%	0.67	3.84	63%

*Notes: Calculated monthly over the test period. All figures are annualized. Two-tail significance: * = 90%, ** = 95%, *** = 99%.*

Source: Research Affiliates, LLC, using data from Bloomberg, Robert Shiller's Online Data, Moody's, and REIT.com.

In the United States and global universes, each of which consists only of mainstream stocks and bonds, value produced the strongest results, while momentum produced a weaker result. Even so, in both universes, the combinations were reasonably competitive when measured on the basis of information ratio and *t*-statistic. This is not the case for the diversified universe, which embraces a broader diversification toolkit of 15 asset classes: Momentum was very helpful, and the combination strategy (all three factors) performed better than any of the individual strategies.

Diversifying by strategy or by universe coincides with a strong upward trend in the alpha *t*-statistics, as shown in Exhibit 4. The least compelling stand-alone alpha strategies—not a surprise—were in the 2-asset U.S.-only universe, averaging a *t*-statistic of 0.47. At the other end of the spectrum, the diversified universe combination strategy delivered a *t*-statistic of over 3.8. In a study that is fastidiously light on data mining, this is a good outcome.

Exhibit 4

Average *t*-Statistic by Universe and Strategy Combination, January 1980–December 2016

	Universe		
	U.S.	Global	Diversified
Single Strategies	0.47	0.62	2.09
Strategy Pairs	0.59	0.88	3.04
Combination	0.73	1.06	3.84

Notes: Calculated monthly over test period. All figures are annualized.

Source: Research Affiliates, LLC, using data from Bloomberg, Robert Shiller's Online Data, Moody's, and REIT.com.

In short, we find that a combination of basic factor strategies, constructed to be implementable in an unlevered framework, produced significantly positive returns when applied to a diversified universe over the 1980–2016 period. This finding supports previous work in this area, particularly that of Blitz and van Vliet [2008]. For more-restrictive universes, such as U.S. or global universes with two and four assets, respectively, the resulting combination strategy alpha was less compelling, lacking significance at a 5% threshold.

A clear implication of our work is that investors can maximize returns by adopting a TAA strategy in as broad a universe as possible. In contrast, first generation TAA strategies, which are limited to U.S. stocks, bonds, and cash, face the challenge of differentiating their alpha from noise. Even applying first generation TAA to global stocks and bonds, and even over very long periods such as considered in this analysis, extracting statistical significance from these simple models is difficult.

We also analyze the correlation structure of the performance of all the strategies, as reported in Exhibit 5. In the diversified universe, each of the three strategies was negatively correlated with the other, in the range of −0.17 to −0.04. This result suggests that blending the three strategies has important benefits, although it is less true for the more-restricted stock/bond universes. Within the global universe, positive (albeit low) correlations exist between strategies, with

EXHIBIT 5

Correlation Matrix between Strategies by Universe, January 1980–December 2016

	Carry	Value	Momentum
U.S. Universe			
Carry	1.00	0.20	−0.16
Value	0.20	1.00	−0.09
Momentum	−0.16	−0.09	1.00
Global Universe			
Carry	1.00	0.29	0.11
Value	0.29	1.00	0.27
Momentum	0.11	0.27	1.00
Diversified Universe			
Carry	1.00	−0.04	−0.15
Value	−0.04	1.00	−0.17
Momentum	−0.15	−0.17	1.00

Notes: Calculated monthly over test period. All figures are annualized.

Source: Research Affiliates, LLC, using data from Bloomberg, Robert Shiller's Online Data, Moody's, and REIT.com.

carry and value demonstrating the strongest relationship (a 0.29 correlation). The U.S. universe was mixed, with carry and momentum exhibiting the most negative correlation at –0.16, while carry and value displayed the highest, and positive, correlation of 0.20.

In Panels A through D of Exhibit 6, we present the cumulative wealth, on a log scale, of the individual and combination strategies for all three universes versus their respective equal-weighted benchmark. Panel A displays the return of the combination strategy and benchmark for the diversified portfolio; Panel B displays the risk-adjusted alpha of the three strategy portfolios for the diversified opportunity set; Panel C displays the excess return of the combination strategy for each of the three universes; and Panel D displays the risk-adjusted alpha of the combination strategy of each of the three universes. In all cases, the more diversified the benchmark and opportunity set, the better the value-add. Panels E and F display the rolling three-year performance—excess return and risk-adjusted alpha—of carry, value, and momentum for the diversified opportunity set.

The negative correlation between the strategies (shown in Exhibit 5), which contributes to the strong results of the combination strategy, is illustrated by the rotation of strategy leadership performance in Exhibit 7. On a monthly basis, strategy leadership rotates among all the strategies from between 28% for carry to 40% for momentum. Value's leadership position is typically (67% of the time) first or second.

ROBUSTNESS CHECKS

In this section, we investigate the robustness of our findings. We first study how the proportion of asset classes that a strategy holds either over- or underweight affects its performance statistics. Second, we investigate how to bridge the gap between the concentrated and diversified portfolios by building a portfolio based on a larger number of asset classes.

To find the main results we reported earlier, we overweighted the asset classes with a percentile score above 50%, which allows the largest number of asset classes for active bets. Prior research on levered strategies typically has adopted a narrower one-third ($\theta = 33\%$) or quartile ($\theta = 25\%$) approach in constructing portfolios. We investigate the result of being more selective by constructing the portfolios positions using the top and bottom thirds, and quarters, of our universes, in addition to the top and bottom halves. The alpha increases with the number of asset classes available for active weights as we raise the threshold from 25% to 50%. The tracking error increases roughly proportionally with the higher number of asset classes, and the information ratios remain quite consistent. We observe, based on the measures reported in Exhibit 8, that a more selective approach makes essentially no difference in the results.

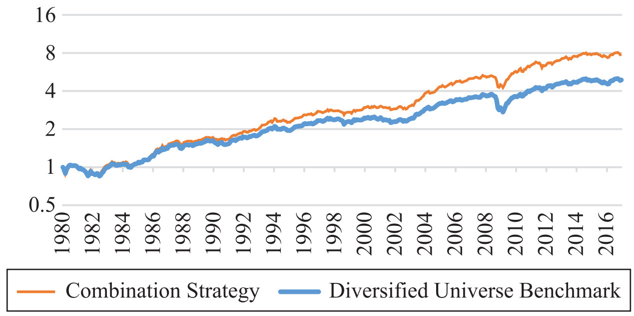
We also perform the same analysis while varying the number of asset classes from our original choice of 2, 4, and 15 to the intervening numbers of asset classes. We construct portfolios by including asset classes in a manner that roughly maintains a similar level of total risk across the portfolios, adding the asset classes in the order listed in Exhibit 1. For example, the sixth portfolio includes all asset classes up to and including the sixth asset listed in Exhibit 1, which are commodities.

As we add more assets, we observe a monotonic increase in the information ratios and t-statistics of the alpha. Alpha meaningfully rises from a low of 23 bps for the 2-asset U.S. universe to 122 bps for the 15-asset diversified universe. We were surprised that the rate of improvement in the information ratios and t-statistics was roughly linear and did not show much sign of waning as more asset classes were added. This leads us to wonder how much benefit may be garnered by an even broader selection of asset classes! Exhibit 9 reports

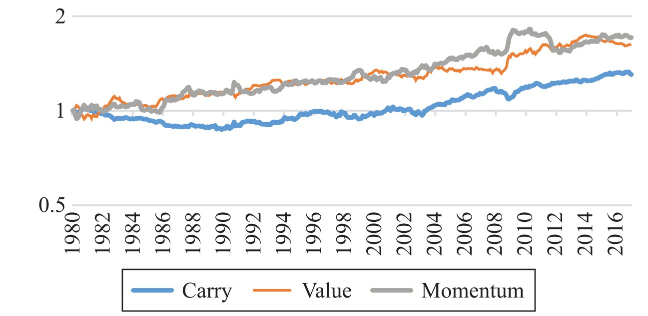
Exhibit 6

Strategy Alpha Performance by Selection Grouping, January 1980–December 2016

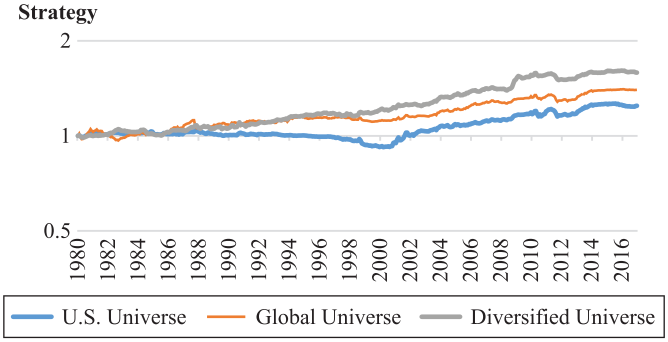
Panel A: Cumulative Return: Combination Strategy vs. Benchmark, Diversified Universe



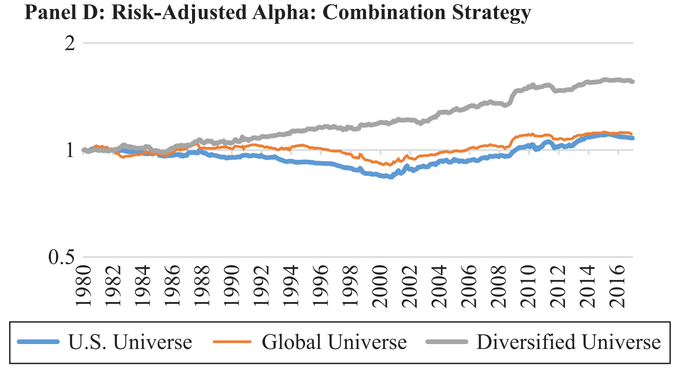
Panel B: Strategy Risk Adjusted Alpha: Diversified Universe



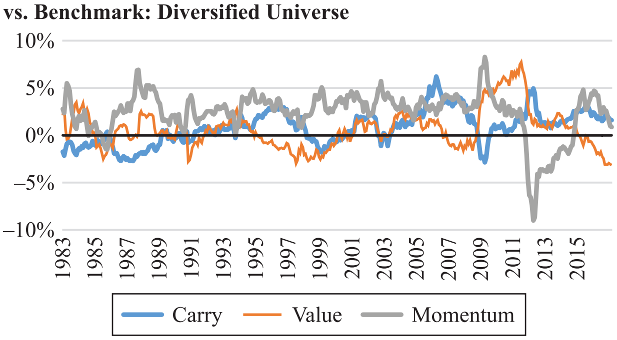
Panel C: Excess Return vs. Benchmark: Combination Strategy



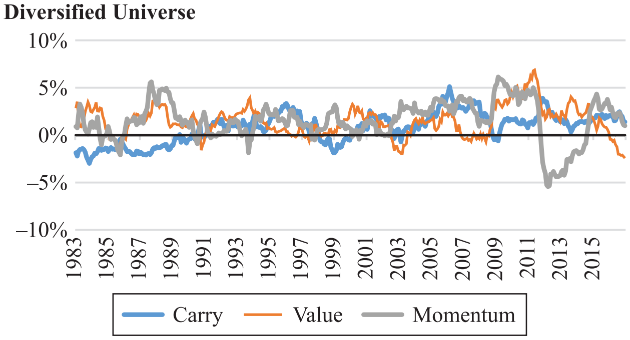
Panel D: Risk-Adjusted Alpha: Combination Strategy



Panel E: Strategy Rolling Three-Year Excess Return vs. Benchmark: Diversified Universe



Panel F: Strategy Rolling Three-Year Risk-Adjusted Alpha: Diversified Universe



Source: Research Affiliates, LLC, using data from Bloomberg, Robert Shiller's Online Data, Moody's, and REIT.com.

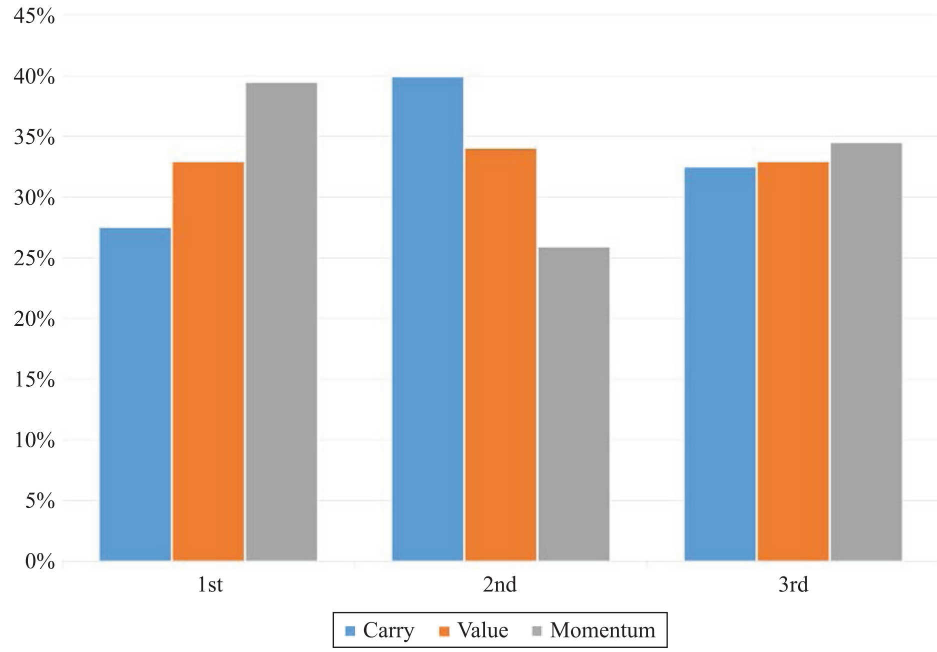
our findings for the strategies as they are constructed with a varying number of asset classes.

CONCLUSION

Our aim has been to test whether we can translate well-known return drivers into an implementable long-only GTAA strategy—as opposed to a hypothetical long/short frictionless paper portfolio—given the practical limitations on leverage, universe composition, and turnover. We find this is entirely possible if a portfolio holds a broadly diversified array of asset classes and maintains a level of turnover consistent with the recommendations of the factor strategies used in the portfolio.

In light of these results, the continued dominance of the policy portfolio and prevalence of the 60/40 domestic stock/bond portfolio is puzzling. Investors seem to be unnecessarily hobbled by their adherence to these benchmarks. A step in the right direction begins with broadening our investment guidelines to permit a benchmark

EXHIBIT 7
Monthly Strategy Leadership



Source: Research Affiliates, LLC, using data from Bloomberg, Robert Shiller's Online Data, Moody's, and REIT.com.

EXHIBIT 8
Strategy Alpha Performance by Selection Grouping, January 1980–December 2016

	Alpha Return	Tracking Error	Info Ratio	*t*-Value	Turnover
Threshold = 25%	0.90%***	1.36%	0.67	3.84	42%
Threshold = 33%	1.03%***	1.48%	0.69	3.99	46%
Threshold = 50%	1.22%***	1.84%	0.67	3.84	63%

*Notes: Calculated monthly over the test period. All figures are annualized. Two-tail significance: * = 90%, ** = 95%, *** = 99%.*

Source: Research Affiliates, LLC, using data from Bloomberg, Robert Shiller's Online Data, Moody's, and REIT.com.

EXHIBIT 9
Carry/Value/Momentum Combination Alpha Performance by Asset Classes, January 1980–December 2016

Asset Classes	Alpha Return	Tracking Error	Info Ratio	*t*-Value	Turnover
2	0.23%	1.80%	0.13	0.73	33%
4	0.32%	1.74%	0.18	1.06	31%
6	0.70%***	1.50%	0.47	2.69	36%
9	0.98%***	1.80%	0.55	3.15	51%
12	0.98%***	1.71%	0.58	3.32	58%
15	1.22%***	1.84%	0.67	3.84	63%

*Notes: Calculated monthly over the test period. All figures are annualized. Two-tail significance: * = 90%, ** = 95%, *** = 99%.*

Source: Research Affiliates, LLC, using data from Bloomberg, Robert Shiller's Online Data, Moody's, and REIT.com.

with additional asset classes and to allow symmetric bets both for and against these asset classes.

Our analysis supports the work of previous authors who conclude that implementing a simple set of factor strategies in an asset allocation framework seems highly effective. Most prior research focuses on strategy implementation in a levered long/short portfolio with a diversified set of asset classes, which is at odds with real-world limitations. In our study, we impose an unlevered implementation across a broad range of investable asset classes with different risk levels. Even though this inherently limits our ability to add significant value, a very simple approach works surprisingly well. Our most important result is that having more asset classes—as long as they are lightly correlated—drives up the excess return almost monotonically, and almost linearly.

Our results may be extended in various ways. Our return drivers for value and momentum are extraordinarily simple; and although our carry signal requires slightly more modeling, it harnesses only historical data. Ours is a deliberately simple test with surprisingly significant results. Although our analysis can be thought of as a robustness check against more-complex definitions of return drivers, further refining of the signals and portfolio construction methods could easily improve the likely alpha of a live unlevered strategy. Indeed it has for many existing strategies; the backtests of those strategies are, however, inherently suspect. A backtest of a hypersimplistic model is far more credible, making its high statistical significance that much more impressive.

APPENDIX

Exhibit A1 displays the excess return—the raw portfolio return in excess of the equal-weight benchmarks—for the individual, pair, and combination strategies for the three universes we study. In the excess return case, all combination strategies are statistically significant at the 10% level, although they possess positive correlation with the benchmarks and thus add value by taking long-term market risk. Our calculation of alpha adjusts for this market risk exposure.

Exhibit A2 displays the regressions for each portfolio and combinations for the factor regressions. The intercept is the alpha, which is the main result of our analysis.

EXHIBIT A1

Unadjusted Strategy Performance by Universe, January 1980–December 2016

	Excess Return	Tracking Error	Info Ratio	*t*-Value	Turnover
U.S. Universe					
Carry	0.33%	3.35%	0.10	0.59	15%
Value	0.36%	3.44%	0.10	0.63	15%
Momentum	1.21%**	3.75%	0.32	1.97	73%
Carry & Value	0.34%	2.63%	0.13	0.79	15%
Carry & Mom	0.77%**	2.31%	0.33	2.03	43%
Value & Mom	0.79%**	2.43%	0.32	1.97	43%
Combination	0.63%*	1.98%	0.32	1.94	33%
Global Universe					
Carry	0.64%	3.14%	0.20	1.24	15%
Value	1.19%***	2.62%	0.46	2.77	19%
Momentum	1.13%**	3.43%	0.33	2.01	67%
Carry & Value	0.92%**	2.32%	0.40	2.4	16%
Carry & Mom	0.89%**	2.45%	0.36	2.2	39%
Value & Mom	1.16%***	2.43%	0.48	2.92	41%
Combination	0.99%***	2.12%	0.47	2.84	31%
Diversified Universe					
Carry	0.87%*	2.99%	0.29	1.77	26%
Value	0.49%	3.67%	0.13	0.82	31%
Momentum	2.49%***	4.69%	0.53	3.23	148%
Carry & Value	0.68%*	2.32%	0.29	1.79	26%
Carry & Mom	1.68%***	2.58%	0.65	3.96	84%
Value & Mom	1.49%***	2.73%	0.55	3.33	86%
Combination	1.29%***	1.93%	0.67	4.05	63%

*Notes: Calculated monthly over the test period. All figures are annualized. Two-tail significance: * = 90%, ** = 95%, *** = 99%.*

Source: Research Affiliates, LLC, using data from Bloomberg, Robert Shiller's Online Data, Moody's, and REIT.com.

Exhibit A2

Factor Regressions by Individual Style and by Combination, January 1980–December 2016

Panel A: Styles

	U.S.			Global			Diversified		
	Carry	Value	Momentum	Carry	Value	Momentum	Carry	Value	Momentum
Intercept	–0.0003	0.0006	0.0002	–0.0003	0.0007*	0.0004	0.0006*	0.0011**	0.0013**
	(–0.60)	(–1.59)	(–0.43)	(–0.98)	(–1.94)	(–0.9)	(–1.72)	(–2.27)	(–2.28)
RMRF	0.0564***	–0.1225***	0.0537***	0.1442***	0.0206**	0.0574***	0.0436***	–0.0944***	0.001
	(–5.31)	(–12.74)	(–4.65)	(–19.36)	(–2.34)	(–5.52)	(–4.85)	(–8.11)	(–0.07)
SMB	0.0384**	0.0585***	–0.0243	0.0109	0.0290**	–0.01	0.0278**	0.0414**	0.0016
	(–2.56)	(–4.31)	(–1.50)	(–1.04)	(–2.33)	(–0.68)	(–2.19)	(–2.52)	(–0.08)
HML	0.0913***	0.0678***	0.0272	0.0488***	0.0449***	–0.0113	0.0506***	0.0058	–0.0023
	(–5.79)	(–4.76)	(–1.59)	(–4.42)	(–3.43)	(–0.73)	(–3.8)	(–0.34)	(–0.11)
MOM	0.0069	0.0005	0.1085***	0.0123*	0.0179**	0.0864***	–0.0205**	–0.0477***	0.1447***
	(–0.69)	(–0.05)	(–9.99)	(–1.76)	(–2.15)	(–8.83)	(–2.42)	(–4.35)	(–11.03)
TERM	–0.0511***	0.0395***	–0.0539***	–0.0828***	–0.0301**	–0.0623***	–0.0692***	0.0324*	–0.0188
	(–3.38)	(–2.88)	(–3.29)	(–7.81)	(–2.39)	(–4.21)	(–5.40)	(–1.96)	(–0.95)
DEF	0.0416	0.0550*	–0.0509	0.0046	–0.0756***	–0.1212***	0.0805***	0.0007	–0.0921**
	(–1.26)	(–1.84)	(–1.42)	(–0.2)	(–2.75)	(–3.75)	(–2.88)	(–0.02)	(–2.12)
R2	17%	35%	22%	53%	6%	24%	25%	17%	27%

Panel B: Combinations

	U.S.				Global				Diversified			
	C, V	C, M	V, M	C, V, M	C, V	C, M	V, M	C, V, M	C, V	C, M	V, M	C, V, M
Intercept	0.0002	0	0.0004	0.0002	0.0002	0	0.0006*	0.0003	0.0009***	0.0010***	0.0012***	0.0010***
	(0.53)	(–0.11)	(1.35)	(0.73)	(0.74)	(0.17)	(1.74)	(1.06)	(2.82)	(2.88)	(3.43)	(3.84)
RMRF	–0.0331***	0.0550***	–0.0344***	–0.0041	0.0824***	0.1008***	0.0390***	0.0741***	–0.0254***	0.0223***	–0.0467***	–0.0166***
	(–3.96)	(7.99)	(–4.61)	(–0.66)	(12.35)	(15.91)	(5.13)	(12.26)	(–3.42)	(2.71)	(–5.51)	(–2.60)
SMB	0.0485***	0.007	0.0171	0.0242***	0.0200**	0.0005	0.0095	0.01	0.0346***	0.0147	0.0215*	0.0236***
	(4.12)	(0.73)	(1.62)	(2.74)	(2.12)	(0.05)	(0.89)	(1.17)	(3.3)	(1.27)	(1.8)	(2.62)
HML	0.0795***	0.0592***	0.0475***	0.0621***	0.0468***	0.0187**	0.0168	0.0274***	0.0282**	0.0242**	0.0018	0.0180*
	(6.43)	(5.8)	(4.29)	(6.69)	(4.74)	(2)	(1.49)	(3.07)	(2.57)	(1.98)	(0.14)	(1.91)
MOM	0.0037	0.0577***	0.0545***	0.0386***	0.0151**	0.0494***	0.0522***	0.0389***	–0.0341***	0.0621***	0.0485***	0.0255***
	(0.47)	(8.89)	(7.74)	(6.55)	(2.4)	(8.28)	(7.29)	(6.84)	(–4.87)	(8.03)	(6.08)	(4.24)
TERM	–0.0058	–0.0525***	–0.0072	–0.0219**	–0.0564***	–0.0726***	–0.0462***	–0.0584***	–0.0184*	–0.0440***	0.0068	–0.0185**
	(–0.49)	(–5.35)	(–0.68)	(–2.45)	(–5.94)	(–8.05)	(–4.27)	(–6.79)	(–1.74)	(–3.76)	(0.57)	(–2.03)
DEF	0.0483*	–0.0046	0.0021	0.0153	–0.0355*	–0.0583***	–0.0984***	–0.0641***	0.0406*	–0.0058	–0.0457*	–0.0036
	(1.86)	(–0.21)	(0.09)	(0.78)	(–1.71)	(–2.96)	(–4.16)	(–3.41)	(1.76)	(–0.23)	(–1.73)	(–0.18)
R2	17%	26%	22%	18%	32%	44%	19%	33%	15%	16%	20%	9%

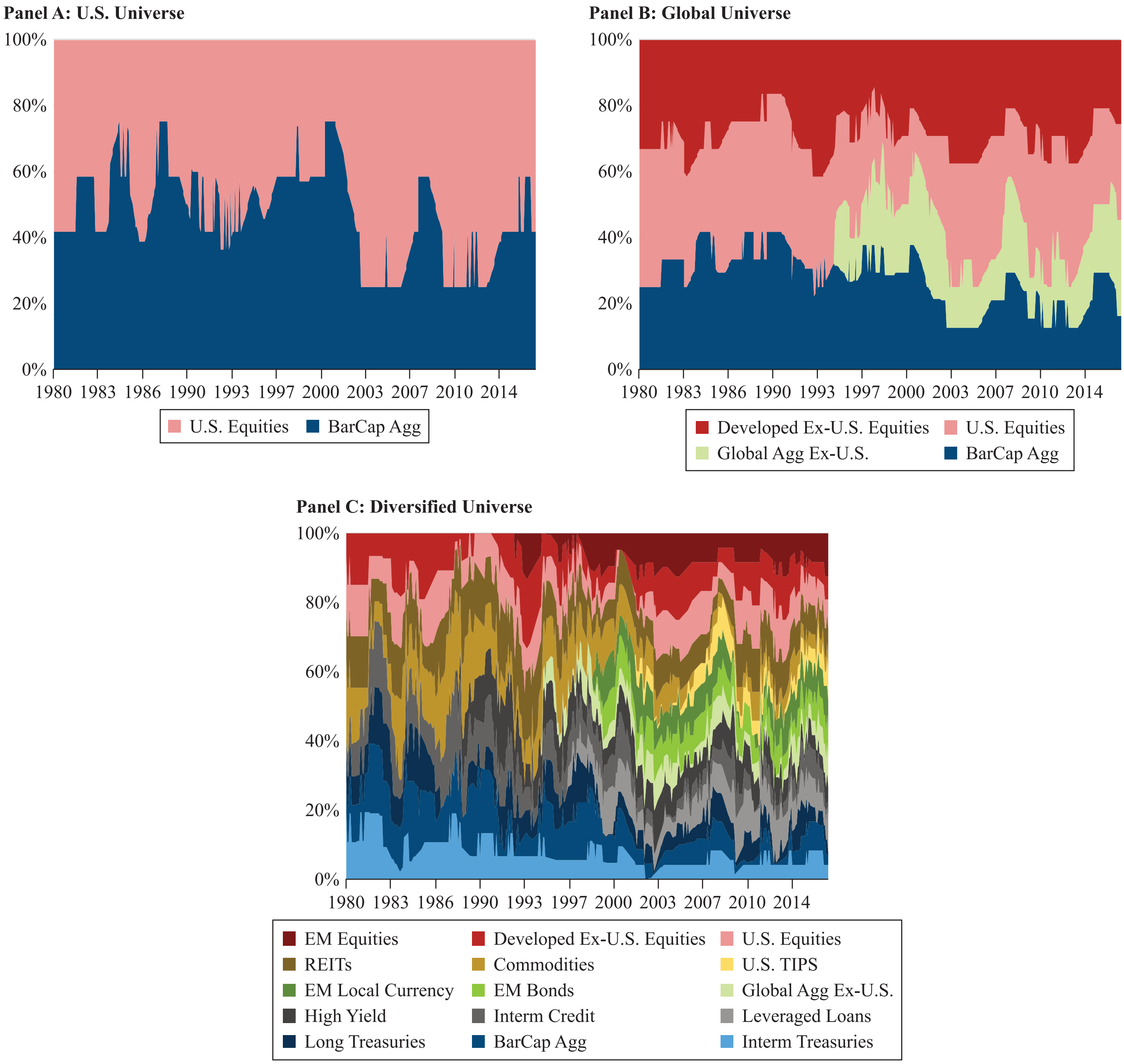
Notes: Calculated monthly over the test period; t-values are in parentheses. C, V is 1/2 (Carry + Value); C, M is 1/2 (Carry + Momentum); V, M is 1/2 (Value + Momentum); and C, V, M is 1/3 (Carry + Value + Momentum).

*Two-tail significance: * = 90%, ** = 95%, *** = 99%.*

Source: Research Affiliates, LLC, using data from Bloomberg, Robert Shiller's Online Data, Moody's, and REIT.com.

E X H I B I T   A 3

Carry/Value/Momentum Combination Portfolio Allocations by Universe, January 1980–December 2016



Source: Research Affiliates, LLC, using data from Bloomberg, Robert Shiller's Online Data, Moody's, and REIT.com.

ENDNOTES

[1]Interest in diversification has recently abated in the face of a protracted bull market in mainstream domestic stocks and bonds, creating the illusion that diversification is unhelpful. In fact, one of our colleagues, Jason Hsu, is fond of describing diversification as a "regret-maximizing" strategy. In a bull market, we regret any investments in diversifying assets because they take us out of our core holdings, whose prices are soaring, but when the inevitable bear market in our core assets arrives, we regret having too little invested in diversifiers.

[2]Because others have thoroughly explored the specifics of optimal time-varying strategies, we do not choose to advance this line of inquiry. Instead, we aim to transparently translate the most studied, robust, and pervasive return factors in the academic community—carry, value, and momentum—into a dynamic unlevered long-only multi-asset portfolio, the natural habitat of global tactical asset allocation, or GTAA.

[3]Our approach is most similar to that of Blitz and van Vliet [2008] and Haghani and Dewey [2016], although they examine GTAA implementations in a long/short or single-benchmark case using different asset classes, weighting programs, and time periods. We also refer the reader to additional work in this space by Wang and Kochard [2012] and Gnedenko and Yelnik [2016]. Although all of these previous analyses have used very different tools, they uniformly support the view that investors can improve investment outcomes by changing asset exposures based on carry, value, and momentum signals.

[4]In our 37-year test period, the asset classes available for investment, and thus for inclusion in the diversified universe, increased from an initial 8 in 1980 to 15 by the end of the period.

[5]Adjusted alpha is adjusted by assessing co-movement with a group of market factors in order to remove the bias that the strategy may be taking a different level of market risk than the average of the benchmark. Blitz and van Vliet [2008] find an unadjusted information ratio, with leverage, of 1.19. This information ratio is comparable to our unadjusted combination portfolio information ratio of 0.67, which is presented in the appendix. Haghani and Dewey [2016] undertake an unlevered application for a broad set of assets with a particular weighting scheme and produce Sharpe ratios of 0.76, in line with our findings for a very diversified portfolio.

[6]We use the return of the Barclays US Long Corporates (Unhedged) minus Barclays US Treasury Long (Unhedged) to construct the default risk factor DEF using data from Bloomberg.

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