Institutional Investor Journals

The Voices of Influence | iijournals.com

The Journal of Portfolio Management

VOLUME 35 NUMBER 1 www.iijpm.com FALL 2008

Global Tactical Cross-Asset Allocation:
Applying Value and Momentum Across Asset Classes

DAVID C. BLITZ AND PIM VAN VLIET

Robeco is an International asset manager offering an extensive range of active Investments, from equities to bonds. Research lies at the heart of everything we do, with a 'pioneering but cautions' approach that has been in our DNA since our foundation in Rotterdam in 1929. We believe strongly in sustainability investing, quantitative techniques and constant innovation.

ROBECO
The Investment Engineers

Global Tactical Cross-Asset Allocation: *Applying Value and Momentum Across Asset Classes*

David C. Blitz and Pim Van Vliet

David C. Blitz
is head of Quantitative Equity Research at Robeco Asset Management in Rotterdam, The Netherlands.
d.c.blitz@robeco.nl

Pim Van Vliet
is a senior researcher at Robeco Asset Management in Rotterdam, The Netherlands.
p.van.vliet@robeco.nl

The objective of global tactical asset allocation (GTAA) is to improve on a given strategic asset allocation by tactically adjusting the weights of asset classes based on their perceived attractiveness. A popular approach to GTAA is to first develop various complementary allocation models, each with a limited scope, that can subsequently be used as building blocks for a comprehensive GTAA strategy.[1] For example, one could start with an equity market timing model, and then add a bond market timing model, global country allocation models (for both equities and bonds), and finally a currency allocation model. The next stage would entail assigning appropriate risk budgets to each of these models in order to obtain the actual GTAA strategy. For a discussion of a comprehensive GTAA risk-budgeting framework, see Sharpe [1987] and Lee [2000]. Existing literature provides many useful leads for developing GTAA building-block models. For example, Fama and French [1989] showed that factors, such as the term spread and dividend yield, contain predictive power for the future equity risk premium. The term spread has also been related to future bond returns; for example, by Fama and Bliss [1987] and Ilmanen [1995]. In equity country allocation, both medium-term momentum and long-term mean reversion have been shown to be effective; see Chan, Hameed, and Tong [2000] and Richards [1995, 1997]. A final example is carry strategies for currencies, as documented by Hodrick [1987] and Froot and Thaler [1990].

The traditional approach simplifies the GTAA problem by breaking it down into several smaller problems, which can be handled separately. Each building-block model considers a limited number of similar assets and takes into account the specific variables considered relevant for a particular allocation decision. But, by not directly comparing each asset to every other asset in the opportunity set, the full potential of GTAA may be left unrealized. Another drawback of the multimodel approach is that it takes a considerable amount of effort to develop the separate building-block models. Thus, in practice, often only a limited number of models are actually employed in GTAA strategies. Furthermore, combining the positions indicated by the different models requires a sophisticated risk-budgeting approach for managing aggregate portfolio risk. These issues are addressed by the alternative approach to GTAA we present in this article. Our approach is characterized by the use of a single model to directly compare the attractiveness of a broad and diverse range of asset classes. We call this approach Global Tactical Cross-Asset Allocation, or GTCAA.

The key issue we address in this article is whether classic cross-sectional return patterns, which have previously been documented at the security level, can also be observed across asset classes. This topic has received surprisingly little attention in the existing literature. Clearly, if the cross section of asset class returns cannot be explained by the current set of pricing models, this would add yet another puzzle to the field of empirical asset pricing. Given that a cross-asset allocation strategy can be implemented relatively easily using a limited number of highly liquid instruments, such as futures, the discovery of a profitable GTCAA strategy would pose a formidable challenge to market efficiency.

Using U.S. stock data, Jegadeesh and Titman [1993] documented a strong 6-month return momentum effect. Fama and French [1996] showed that many U.S. stock market effects can be explained by exposure to size and value premiums, with the exception of 12-1 month momentum. Fama and French [1998] and Rouwenhorst [1998] also documented value and momentum premiums for international stock markets. Pirrong [2005], one of the few authors to take a cross-market perspective, reported significant profits for 3- to 12-month price momentum strategies applied to futures markets. Interestingly, mixed results have been found for portfolios based on past 1-month returns. Jegadeesh [1990] found a short-term reversal effect at the stock level, while Moskowitz and Grinblatt [1999] found a short-term momentum effect at the industry level.

We examine value and momentum strategies for tactical allocation across a broad range of asset classes.[2] Applying price momentum to cross-asset allocation is relatively simple because the strategy only requires past returns as inputs. We consider both a 12-1 month momentum strategy and a strategy based on 1-month returns. Constructing a cross-asset allocation value strategy is less straightforward, because no obvious valuation measure is applicable to every asset class. The essence of our valuation strategy is to compare asset classes using relatively simple yield measures. We describe our approach in detail in the methodology section.

Our main finding is that the application of momentum and value strategies to global tactical asset allocation across 12 asset classes delivers statistically and economically significant abnormal returns. We document return premiums between 7% and 8% for the 1-month momentum, 12-1 month momentum, and value GTCAA strategies over the 1986–2007 period. Interestingly, the 1-month momentum effect is in line with previous findings at the industry level, but is contrary to the reversal effect, reported at the stock level. For a GTCAA strategy based on a simple combination of momentum and value factors, we find an alpha of 12% a year. Performance is stable over time, present for a reduced set of assets over the 1974–1985 period, and sufficiently high to overcome transaction costs in practice. Furthermore, the performance is robust to adjustments for implicit market exposures and is also largely unaffected by adjustments for implicit loadings on the CAPM market factor, Fama–French size and value factors, and Carhart momentum factor.

Our findings are relevant for both theoretical and practical reasons. From a theoretical perspective, our findings may challenge market efficiency and market equilibrium. Furthermore, our results imply that value and momentum effects are present not only within a specific asset class, but also across entire asset classes. Although no generally accepted asset pricing model applies to the wide variety of asset classes considered in this article, we argue that any such model is unlikely to explain the return effects found in our analysis. Interestingly, the momentum and value effects that we observe across different asset classes are similar in magnitude, but only partly related to the momentum and value effects that have been previously documented within asset classes, and for which behavioral explanations have been put forward. Thus inspired, we also provide a possible behavioral explanation for the momentum and value effects that we observe across asset classes.

Our results are interesting for practitioners, because they provide a single-model approach to GTAA, which may be used as either an alternative to multimodel GTAA strategies or as an additional building block for such strategies. One of the limitations of our cross-asset allocation approach is that it cannot easily incorporate asset-specific variables. For example, analysts' earnings revisions might be a relevant factor for equity markets, but bond markets lack an obviously equivalent measure. Hence, with GTCAA, the focus is more on breadth (covering many assets with a limited set of factors) than on depth (covering a single allocation decision with many asset-specific factors).

The article is organized as follows. In the next section, we describe the data and methodology, then present the main results for momentum and valuation strategies applied to global tactical cross-asset allocation. The subsequent section contains various robustness tests, followed by a discussion of the possible explanations for our findings. The final section concludes and reviews the implications for investors.

DATA AND METHODOLOGY

Exhibit 1 is an overview of the 12 asset classes that constitute the opportunity set for our analyses and the indices that we use to measure the returns of these asset classes. Three of the asset classes relate to the U.S. equity market, namely, U.S. large-cap equity, U.S. mid-cap equity, and U.S. real estate equity (REITs). Three represent international equity markets, specifically, the U.K. Japan, and emerging markets. Three are U.S. bond asset classes, namely U.S. Treasuries, U.S. investment-grade bonds, and U.S. high-yield bonds, and two are the main international bond markets, Germany and Japan. The final asset class is a U.S. 1-month LIBOR cash investment, which serves as our proxy for the risk-free alternative.

Although the selection of the asset classes was not based on a formal set of rules, we did consider a number of criteria; in particular, which asset classes *not* to include. We eliminated those asset classes

- with less than 20 years of data history (e.g., emerging markets debt and hedge funds);
- which are more difficult to model, especially with regard to valuation (e.g., commodities and currencies);
- which are illiquid and/or lack market prices (e.g., direct real estate and private equity);
- with a limited market capitalization and/or limited economic relevance (e.g., micro-cap stocks);
- which are highly correlated and would reduce the heterogeneity of the investment universe (e.g., the inclusion of each of the 20 largest stock markets as separate assets).[3]

For each asset class, except emerging markets equity, we subtract the local risk-free return (i.e., U.S., U.K., Japan, or German 1-month LIBOR) from the total return in local currency. The excess return resembles the return that can be obtained in practice with futures contracts, although futures contracts are (or were) not actually available in practice for all assets.[4] For emerging markets equity, we use open (unhedged) returns in U.S. dollars in excess of the U.S. 1-month LIBOR return.

The earliest date for which return data is available for every asset class in our universe is January 1985. Because 12-1 month momentum is a strategy we analyze, our analysis effectively starts at the end of January 1986. This is also the first month for which valuation data is available for every asset class. The last month of our sample period is September 2007. Exhibit 2 summarizes the risk and return characteristics of each asset class over the full sample period. Average annual excess returns vary between less than 1% (Japan equity) and almost 11% (emerging markets equity). Sharpe ratios for the individual asset classes vary between 0.03 (Japan equity) and 0.56 (U.S. investment-grade bonds).

EXHIBIT 1
Indices Used

Asset Class	Index	Start Date
U.S. large-cap equity	S&P500[1]	Jan-70
U.S. mid-cap equity	S&P400[2]	Feb-73
U.S. real estate equity	FTSE/NAREIT	Feb-72
U.K. equity	FTSE100[3]	Jan-70
Japan equity	TOPIX	Feb-73
U.S. Treasury bonds	Lehman U.S. Treasury	Feb-73
U.S. investment-grade bonds	Lehman U.S. Corporate Investment Grade	Feb-73
Cash (risk-free)	1M LIBOR	Jan-70
Emerging markets equity	S&P/IFC Investable Emerging Markets	Jan-85[4]
U.S. high-yield bonds	Lehman U.S. High-Yield[5]	Jan-80
German government bonds	Citigroup Government Bond, Germany	Jan-85
Japan government bonds	Citigroup Government Bond, Japan	Jan-85

Source: [1]Before 1988, Datastream calculated; [2]Datastream calculated; [3]before 1986, MSCI U.K; [4]before 1989, S&P/IFC Global Emerging Markets (valuation data for emerging markets equity starts in Jan-86); [5]before 1987, Merrill Lynch High-Yield 175.

At the end of every month, we rank all assets based on their momentum and/or valuation scores. We use this ranking to assign the assets to four quartile portfolios consisting of three assets each. We then calculate the return of each quartile portfolio over the following month. In addition to the four long-only quartile portfolios, we also consider a long top-quartile and short bottom-quartile zero-investment portfolio. This process is repeated until the end of the sample period. Transaction costs are not included in the initial strategy evaluation, but are discussed separately in a sensitivity analysis.

Our methodology is consistent with classic empirical studies of cross-sectional return patterns at the security level. The fact that our long/short portfolio effectively consists of three pair trades is also conceptually consistent with the theoretical result in Lee [2000], that is, optimal bet sizes in TAA strategies are directly driven by the pairwise differences in expected returns of assets.[5] Our pair trades may consist of traditional TAA bets, such as long U.S. large-cap equity and short U.S. Treasuries, but they can also be less conventional, such as long U.S. real estate equity and short Japanese government debt. Instead of a weakness, this may actually be a strength of our cross-market approach. In the discussion section, we argue that inefficiencies may arise at the asset class level, because many investors perceive full-fledged global tactical asset allocation to be too challenging. We also note that when stand-alone long/short timing strategies are applied to the individual assets within a broadly diversified strategic allocation,[6] the net outcome may well consist of some unconventional pair trades.

We examine both a 1-month return strategy and a classic 12-1 month (12 months, excluding the most recent month) momentum strategy. Only return data is required for these analyses. In addition to the two momentum strategies, we also consider a cross-asset valuation strategy. This strategy is less straightforward, as it requires valuation data that can be used for making direct cross-sectional comparisons of asset classes. The starting point of our approach is a simple yield measure for each asset class. We use the (trailing) earnings yield (E/P ratio) for equity assets, and the standard yield-to-maturity for bond assets.[7] Both yield measures are adjusted for the appropriate (local) risk-free rate of return, as shown in the third column of Exhibit 3. Note that for the bond assets, this means we are effectively using the term premium as our valuation indicator.

The simplicity of using these basic yield measures is appealing, but we question if meaningful comparisons of different asset classes can be made with such an elementary approach. Indeed, it is not difficult to illustrate that this approach is overly simplistic and needs to be refined. Consider, for example, the yield on U.S. high-yield bonds versus that on comparable U.S. Treasury bonds. Obviously, the difference should always be positive, as investors require compensation for being exposed to default risk. Thus, an adjustment for default risk should be made in order to prevent U.S. high-yield bonds from being structurally preferred to U.S. Treasuries. Without

EXHIBIT 2

Risk–Return Characteristics, February 1986 to September 2007

Asset Class	Geometric Mean	Standard Deviation	Sharpe Ratio
U.S. large-cap equity	6.6%	14.8%	0.45
U.S. mid-cap equity	6.7%	15.6%	0.43
U.S. real estate equity	5.3%	12.9%	0.41
U.K. equity	3.5%	15.6%	0.22
Japan equity	0.7%	19.6%	0.03
U.S. Treasury bonds	2.1%	4.7%	0.44
U.S. investment-grade bonds	2.7%	4.9%	0.56
Cash (risk-free)	0.0%	0.0%	n.a.
Emerging markets equity	10.8%	23.0%	0.47
U.S. high-yield bonds	3.4%	7.3%	0.47
German government bonds	1.4%	3.3%	0.43
Japan government bonds	2.2%	4.0%	0.55

Note: Based on annualized excess returns.

EXHIBIT 3
Valuation Measures

Asset Class	Valuation Measure	Reference Point	Average without Extra Hurdle	Extra Hurdle	Average with Extra Hurdle
U.S. large-cap equity	E/P	U.S. 1M LIBOR	–0.2%	-	–0.2%
U.S. mid-cap equity	E/P	U.S. 1M LIBOR	0.6%	-	0.6%
U.S. reale state equity	D/P	U.S. 1M LIBOR	2.5%	2%	0.5%
U.K. equity	E/P	U.K. 1M LIBOR	–1.0%	-	–1.0%
Japan equity	E/P	Japan 1M LIBOR	–0.2%	-	–0.2%
U.S. Treasury bonds	Yield	U.S. 1M LIBOR	0.9%	1%	–0.1%
U.S. investment-grade bonds	Yield	U.S. 1M LIBOR	2.2%	2%	0.2%
Cash (risk-free)	1M LIBOR	U.S. 1M LIBOR	0.0%	-	0.0%
Emerging markets equity	E/P	U.S. 1M LIBOR	0.9%	1%	–0.1%
U.S. high-yield bonds	Yield	U.S. 1M LIBOR	6.2%	6%	0.2%
German government bonds	Yield	German 1M LIBOR	0.7%	1%	–0.3%
Japan government bonds	Yield	Japan 1M LIBOR	0.6%	1%	–0.4%

such an adjustment, U.S. high-yield bonds would be in the top-quartile value portfolio 93% of the time. For other assets, the need to adjust the basic yield measure might be less obvious, but equally necessary. For example, yields on government bonds are not necessarily directly comparable to those on stocks.

For our valuation strategy, we apply a limited number of asset-specific, fixed adjustments to the basic yield data. The following adjustments were chosen in such a way that the main structural biases toward certain asset classes were removed:

- for U.S. Treasuries and German and Japanese government bonds, we subtracted 1% from the term premiums to adjust for an upward-sloping yield curve;
- for U.S. investment-grade credits, we subtracted 2%, and for U.S. high-yield bonds 6%, to adjust for the slope of the yield curve and to adjust for default risk;
- for emerging markets equity, we subtracted 1% to adjust for the asset class's structurally lower P/E compared to mature equity markets;
- for U.S. real estate equity, we subtracted 2% to adjust for the asset class's structurally higher yield compared to other types of equity.

By comparing the average valuation scores before and after these adjustments, shown in the second-to-last and last columns of Exhibit 3, we see that these adjustments result in scores that are much more comparable across asset classes. In fact, after applying the adjustments, the long-term average valuation score for every asset falls between –1% and +1%, which implies that structural biases toward certain asset classes are effectively eliminated.[8]

Given the valuation scores, the valuation investment strategy is tested similarly to the momentum strategies discussed earlier, that is, based on quartile portfolios with a monthly rebalancing frequency. To better understand the interaction between the valuation and momentum effects, we also analyze a combined investment strategy. A combined score for each asset class is calculated by taking a weighted average of its rank (1 to 12) on the individual variables. We choose a simple 50/50 balance between the momentum and valuation strategies and an equal weighting of the two momentum variables. This translates into weights of 25% for 1-month momentum, 25% for 12-1 month momentum, and 50% for valuation.[9] The correlation structure of the three underlying strategies, which is discussed in the next section, provides an additional motivation for this choice of weights.

MAIN RESULTS

The main results of our analysis are presented in Exhibit 4. The top (first) quartile portfolios for the 1-month momentum, 12-1 month momentum, and valuation strategies generate relatively high returns and Sharpe ratios, while the bottom (fourth) quartile portfolios are associated with the lowest returns and Sharpe ratios. The second and third quartile portfolios tend to fall neatly in between, resulting in a monotonic performance pattern over the four quartile portfolios. The long top-quartile and short bottom-quartile (Q1-Q4) zero-investment portfolio generates positive

E X H I B I T 4

Main Results for Value, Momentum, and Combination Strategies, February 1986 to September 2007

	Q1	Q2	Q3	Q4		Q1-Q4
1-month Momentum						
Mean return	9.9%	3.9%	–0.7%	3.0%	Outperformance	6.9%
Standard deviation	10.7%	7.0%	8.0%	11.1%	Tracking error	12.0%
Sharpe ratio	0.93	0.57	0.09	0.27	Information ratio	0.57
					T-statistic	2.67***
12-1 Month Momentum						
Mean return	8.1%	4.0%	3.9%	0.2%	Outperformance	7.9%
Standard deviation	11.6%	8.1%	6.9%	10.7%	Tracking error	13.0%
Sharpe ratio	0.70	0.49	0.56	0.02	Information ratio	0.61
					T-statistic	2.82***
Valuation						
Mean return	8.9%	3.3%	3.0%	1.0%	Outperformance	7.9%
Standard deviation	9.1%	7.7%	7.9%	12.5%	Tracking error	13.2%
Sharpe ratio	0.98	0.42	0.37	0.08	Information ratio	0.60
					T-statistic	2.79***
Combination Strategy						
Mean return	10.4%	6.2%	1.4%	–1.6%	Outperformance	11.9%
Standard deviation	8.7%	7.6%	9.4%	9.9%	Tracking error	10.0%
Sharpe ratio	1.19	0.81	0.14	–0.16	Information ratio	1.19
					T-statistic	5.56***

Note: Annualized log excess returns.

annualized returns of 6.9% for 1-month momentum, 7.9% for 12-1 month momentum, and 7.9% for valuation, which are all statistically significantly different from zero at the 1% significance level. Interestingly, the 1-month momentum effect is in line with previous findings at the industry level, but is contrary to the reversal effects which are reported at the stock level. Furthermore, the GTCAA 12-1 month momentum effect is similar in magnitude to the U.S. stock market momentum effect (UMD, 8.4% for our sample), while the GTCAA value effect is even larger than the value effect within the U.S. stock market (HML, 3.4% for our sample). We conclude that all three variables exhibit significant predictive power for global tactical cross-asset allocation purposes.

The two momentum strategies exhibit a positive correlation with each other of 0.3, and negative correlations of –0.1 to –0.3 with the valuation strategy. These relatively low correlations indicate that we are capturing three distinct effects. The correlation structure also provides an additional motivation for our choice of weights in the combined strategy, as it is reasonable to reduce the weight of variables that are positively correlated (momentum strategies) and increase the weight of variables that exhibit a negative correlation (valuation strategy). Given the relatively low correlations, it is not surprising that the performance of the combined strategy is superior to each of the underlying strategies. The top-quartile portfolio for the combined strategy outperforms the top-quartile portfolios of the underlying strategies. And for the bottom-quartile portfolio of the combined strategy, we find the lowest returns. This results in a return of 11.9% a year for the long/short combined strategy, which is highly significant with a *t*-statistic of well over 5. The volatility of the strategy is 10%, which falls between the volality of equity and bonds, and results in an information ratio of 1.2. Exhibit 5 shows the cumulative returns of both the combined and individual strategies over time. Performance is quite stable over time and is not concentrated in just the early years of the sample.

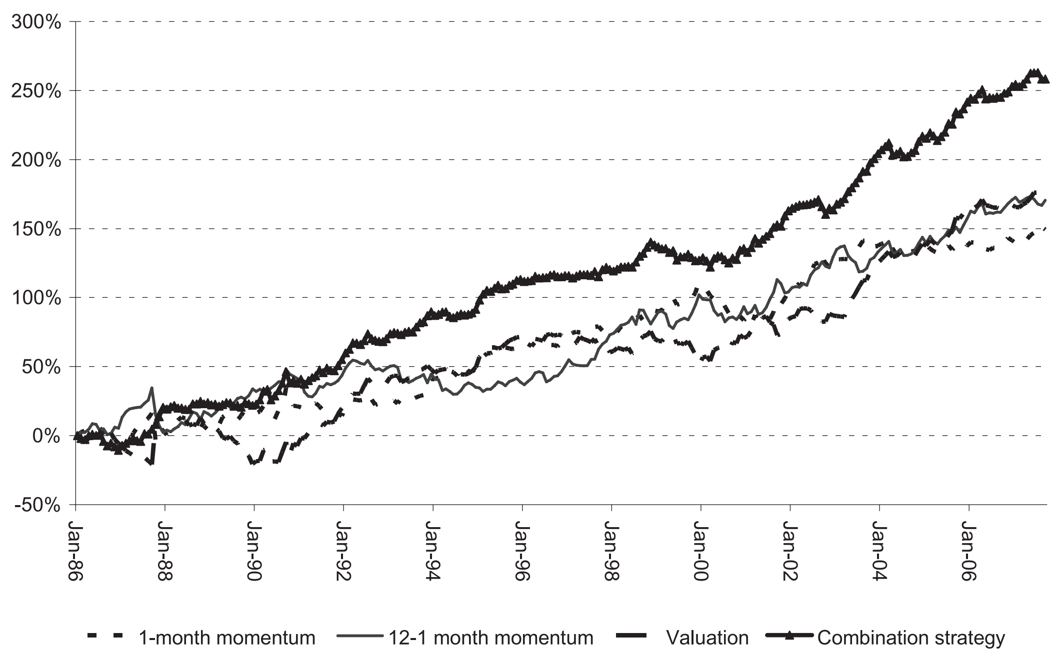
Next, we examine if the returns of the strategies can be explained by structural biases toward certain asset classes. Consider a naïve portfolio, which goes systematically long in equities and short in cash; the return captured by this portfolio simply reflects the equity risk premium. Thus, our concern is that the quartile portfolios may have structurally different exposures to the risk premiums that are offered by the various asset classes. The importance of adjusting for such structural biases is also stressed by Lee [2000]. For the combined strategy, we look at the frequency with which each asset class is selected for each of the quartile portfolios. Exhibit 6 shows that the asset class selected most frequently in the top-quartile portfolio is U.S. real estate equity (REITs), while U.K. equity tends to be the least favored asset class. We also observe that each asset class occurs in each of the quartile portfolios in at least 3% of the observations, and no asset class appears in any quartile portfolio more than 43% of the time.[10] This indicates that the combined value-momentum GTCAA strategy does not have a large structural bias toward a specific asset class.

More formally, we calculate the average net exposure for each portfolio to each of the 12 asset classes, measured ex post over the entire sample period. Using these weights, we create static reference portfolios, which, by definition, exhibit the same average exposures to the various asset classes as the original portfolios. By subtracting the returns of these reference portfolios from the returns of the original portfolios, we effectively adjust the latter for possible systematic biases toward certain asset classes. The Q1-Q4 return of the combination strategy remains at 11%, again with a highly significant *t*-statistic larger than 5. Thus, we conclude that the results are generally robust to the adjustments for implicit systematic biases toward certain asset classes.

Exhibit 7 illustrates how we adjust the (raw) GTCAA strategy returns for their implicit loadings on the classic CAPM market factor, Fama–French size and value factors, and Carhart momentum factor.[11] These regressions allow us to determine if the GTCAA momentum and valuation returns are unique effects, or simply a cross-asset manifestation of effects that are already known to exist within the U.S. stock market.

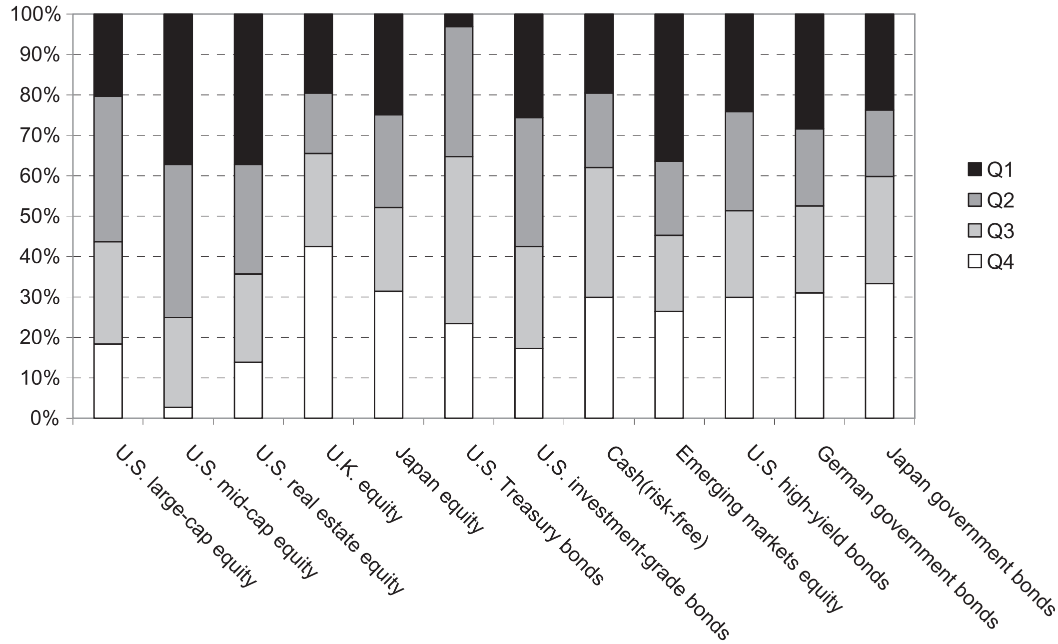
Exhibit 7 shows that a CAPM adjustment does not materially affect the returns of the strategies. The value strategy has a negative loading on the CAPM market factor, while the 12-1 month momentum strategy has a positive beta with regard to the market factor; but these exposures, however, do not subsume their returns. The alphas also remain strong when the Fama–French three-factor adjustment is applied. Interestingly, the GTCAA valuation strategy appears to be weakly related to the Fama–French value (HML) and

EXHIBIT 5
Cumulative Return for Q1-Q4 Strategies



E X H I B I T 6

Average Distribution Across Quartiles for Each Asset Class



size (SMB) factors. The loading on HML suggests that the GTCAA value effect is, to a limited degree, related to the classic value effect within the U.S. stock market. This relationship is not very dominant, however, as the alpha of the GTCAA valuation strategy drops by only about 1%. The same observations apply to the GTCAA combination strategy.

The Fama–French/Carhart four-factor adjustments reveal that the 12-1 month momentum strategy is strongly related to the 12-1 month stock momentum factor (UMD). The GTCAA 12-1 month momentum alpha is, in fact, subsumed to a large degree and becomes insignificant, after adjusting for the UMD momentum factor. Thus, the 12-1 momentum GTCAA strategy is picking up a cross-asset allocation momentum effect, which is closely related to the well-known momentum effect within the U.S. stock market. [12] As both UMD and the cross-market 12-1 month momentum strategy earn premiums of 8% over the sample period, UMD could possibly be mimicked with our cross-market 12-1 month momentum strategy. The UMD momentum premium is difficult to capture in reality, because it involves frequent trading in many hundreds of individual stocks. Our cross-market strategy, however, involves only 12 highly liquid asset classes and is a much easier strategy to put into practice. The GTCAA 1-month momentum strategy is not affected by a UMD correction.

The GTCAA valuation strategy exhibits a strong negative loading on the momentum factor, which strengthens its four-factor alpha. For the GTCAA combined strategy, these effects offset each other, as in this case the effective exposure to the momentum factor is insignificant. As a result, the alpha of the GTCAA combined strategy is robust to CAPM, and three-factor and four-factor model adjustments, and remains very strong at 11%–12% a year.

ROBUSTNESS TESTS

In this section, we further examine the robustness of our findings. First, we analyze the impact of transaction costs. We begin by calculating the amount of turnover associated with the Q1-Q4 strategies. The maximum annual (monthly) turnover is 2400% (200%) one-way, in the event that all long and short positions are replaced every month.[13] Exhibit 8 shows that the annual turnover varies from about 200% for the valuation strategy to 1600% for the 1-month momentum strategy. In order to translate the turnover figures into an estimate of annual transaction costs, we need to assume a certain level of

EXHIBIT 7

CAPM, Fama–French Three-Factor Model, and Fama–French/Carhart Four-Factor Model Adjusted Results for Q1-Q4 Strategies, February 1986 to September 2007

	Alpha	Rm	SMB	HML	UMD
1-Month Momentum					
CAPM	6.9%	0.00			
	*2.64****	*–0.05*			
Fama–French three-factor model	6.8%	–0.02	0.16	0.03	
	*2.56***	*–0.27*	*2.31***	*0.40*	
Fama–French/Carhart four-factor model	6.3%	–0.01	0.15	0.04	0.05
	*2.32***	*–0.14*	*2.21***	*0.49*	*0.92*
12-1 Month momentum					
CAPM	6.9%	0.12			
	*2.48***	*2.20***			
Fama–French three-factor model	6.5%	0.13	0.11	0.08	
	*2.27***	*2.10***	*1.49*	*0.86*	
Fama–French/Carhart four-factor model	2.0%	0.19	0.06	0.15	0.41
	0.78	*3.58****	*0.89*	*1.83**	*8.57****
Valuation					
CAPM	9.6%	–0.21			
	*3.42****	*–3.90****			
Fama–French three-factor model	8.5%	–0.17	0.14	0.18	
	*2.99****	*–2.77****	*1.94**	*1.99***	
Fama–French/Carhart four-factor model	11.2%	–0.21	0.17	0.14	–0.25
	*4.03****	*–3.56****	*2.46***	*1.59*	*–4.83****
Combination Strategy					
CAPM	12.4%	–0.07			
	*5.75****	*–1.59*			
Fama–French three-factor model	11.0%	–0.01	0.17	0.23	
	*5.11****	*–0.25*	*3.02****	*3.37****	
Fama–French/Carhart four-factor model	11.0%	–0.01	0.17	0.23	0.00
	*4.98****	*–0.23*	*3.00****	*3.36****	*0.07*

Note: T-Statistics are in italics.

transaction costs for individual trades. Instead of choosing one particular level of transaction costs per trade, we consider three different levels—10 bps, 25 bps, and most conservatively, 50 bps. The 10 bps figure represents a realistic estimate should the strategies be implemented using highly liquid instruments, such as futures. As this assumption may be too optimistic based on historical experience, we also consider more conservative transaction cost levels.

Exhibit 8 shows estimated returns after transaction costs for the Q1-Q4 strategies. Comparing these results to the results before costs in Exhibit 4, we see that transaction costs are critical for the high-turnover 1-month momentum strategy. At a cost level of 10 bps, about half the performance of the strategy is lost, and performance is completely wiped out if costs are assumed to be more than 20 bps per trade. Not surprisingly, the slower 12-1

Exhibit 8

Annualized Turnover and Returns after Transaction Costs for Q1-Q4 Strategies

	Turnover	Performance after Transaction Costs of			
		–	0.10%	0.25%	0.50%
1-Month Momentum	1675%	6.9%	3.5%	–1.5%	–9.9%
12-1 Month Momentum	491%	7.9%	6.9%	5.4%	3.0%
Valuation	234%	7.9%	7.5%	6.8%	5.6%
Combination Strategy	728%	11.9%	10.5%	8.3%	4.6%

Note: Turnover is one way.

month momentum and valuation strategies are less sensitive to transaction costs. For example, at a cost of 25 bps per trade, only a third of the performance of the 12-1 month momentum strategy is lost, and only about 15% of the performance of the valuation strategy. The combined strategy is well able to survive a realistic level of transaction costs; even with transaction costs of 50 bps per trade, outperformance of 5% a year remains. It is likely that in practice the return can be improved significantly by considering more sophisticated buy/sell rules, or by a portfolio optimization that (a.o.) is able to trade off gross expected returns against the transaction costs associated with trading. These extensions are beyond the scope of this article. We conclude that a GTCAA strategy can generate sufficient performance to overcome the transaction costs that would be incurred in a real-world implementation.

A second robustness test is a pre-sample test over the period January 1974 to January 1986. Data for the last four asset classes in Exhibit 1—emerging markets equity, U.S. high-yield bonds, German government bonds, and Japanese government bonds—are not available for this period. As a result, the number of asset classes drops to eight, and each quartile portfolio consists of only two, instead of three, asset classes. Exhibit 9, which is similar in structure to Exhibit 4, shows that the returns of the various GTCAA strategies tend to be somewhat lower, but still strong, over this out-of-sample period.

A third robustness test examines the effects of using asset class returns adjusted for their respective volatility. Obviously, some assets exhibit much more volatility than others. As a result, the returns of equally weighted portfolios of assets could be dominated by the positions taken in the most volatile assets, such as emerging markets equity. The most volatile assets are also most likely to be either the most or least attractive on a measure such as momentum, because these assets tend to produce the most extreme returns. To avoid these effects, we apply asset-specific volatility adjustments, which are intended to make the asset classes more comparable.[14] At the end of every month, each asset's annualized volatility over the past 60 months is used to lever or de-lever the position in that asset over the next month to an (arbitrary) target volatility level of 10%.[15] For example, if the trailing volatility of emerging markets equity is 20% versus only 5% for U.S. Treasuries, we take half the regular position in emerging markets equity and double the regular position in U.S. Treasuries.

Exhibit 10 shows that the results for this approach remain strong. The Q1-Q4 return for the momentum and valuation strategies on a stand-alone basis is in the 4%–7% range, and for the combined strategy, it is about 9%. Although this initially appears to be lower than for the original strategy, the volatility associated with the alternative approach is also somewhat lower. Thus, both approaches exhibit the same information ratio of 1.2. The results are clearly robust to the methodological choice of whether it is appropriate to adjust asset returns for their volatility.

A final concern that we address is whether the return of the cross-asset allocation strategies might be driven by just one asset class or only a few. The strategy, however, passes this robustness test without problems. Exhibit 11 shows the average monthly return for each asset class, conditional on its quintile classification in the combined strategy. Most asset classes earn an average excess return of at *least* 0.3% during the months that they are top ranked, with a median of 0.8% across the different asset classes. During the months that they are bottom ranked, all asset classes, with the sole exception of U.S. mid-cap equities,[16] earn an average excess return of at *most* 0.2%, with a median of zero. Based on these results, we conclude that the valuation and momentum effects are driven by all asset classes and clearly not by only one or a few.

EXHIBIT 9
Out-of-Sample Test, January 1974 to January 1986

	Q1	Q2	Q3	Q4		Q1-Q4
1 Month Momentum						
Mean return	4.7%	5.3%	–0.6%	0.8%	Outperformance	3.9%
Standard deviation	13.7%	10.2%	11.9%	14.6%	Tracking error	13.4%
Sharpe ratio	0.35	0.51	–0.05	0.06	Information ratio	0.29
					T-statistic	1.01
12-1 Month Momentum						
Mean return	2.7%	4.3%	5.2%	–2.2%	Outperformance	5.0%
Standard deviation	12.2%	11.3%	11.2%	17.3%	Tracking error	18.7%
Sharpe ratio	0.23	0.38	0.47	–0.13	Information ratio	0.27
					T-statistic	0.92
Valuation						
Mean return	9.1%	3.5%	–4.8%	2.5%	Outperformance	6.6%
Standard deviation	15.3%	13.2%	9.8%	11.9%	Tracking error	14.4%
Sharpe ratio	0.60	0.26	–0.49	0.21	Information ratio	0.46
					T-statistic	1.59
Combination Strategy						
Mean return	8.0%	4.1%	–1.0%	–0.7%	Outperformance	8.8%
Standard deviation	13.2%	13.2%	10.5%	12.7%	Tracking error	12.7%
Sharpe ratio	0.61	0.31	–0.10	–0.06	Information ratio	0.69
					T-statistic	2.39**

Note: Tests were performed using only eight asset classes.

DISCUSSION

We continue with a discussion of possible explanations for our empirical finding that simple momentum and valuation strategies seem highly effective for global tactical asset allocation across asset classes. Our findings may simply be the result of chance or overenthusiastic data mining. Should this be true, the relationships we document would likely break down in the future, and the alpha opportunity would turn out to be an illusion. Although it is impossible to rule out, we do not consider this explanation likely, because the strategies we analyze are very basic by design, and the statistical significance of the results is quite strong.

Another explanation for our findings might be that we are capturing time-varying risk premiums on the different asset classes and/or that we are not properly adjusting the strategy returns for risk. For example, suppose each asset class can be in either a state of high expected return combined with high risk or a state of low expected return and low risk. A strategy which implicitly goes long in assets that tend to be in the high-risk state and goes short assets that tend to be in the low-risk state might seem to be capturing alpha, but in fact the returns being generated simply represent a fair compensation for risk.

We cannot rule out this explanation, but it seems unlikely. The degree of time-variation in risk of the asset classes would have to be quite large to justify the return spread of 12% a year that we found for the combined strategy. The results are so strong that for the bottom-quartile portfolios long-term excess returns are close to zero or even negative, even though time-varying risk premiums should remain positive at all times. Furthermore, no evidence of increased risk exists for the high-return top-quartile portfolio of assets compared to the low-return bottom-quartile portfolio in terms of volatility, skewness, or other measures (statistics not reported).

Exhibit 12 Compares the return of the GTCAA strategies, conditional on different macroeconomic regimes. For this analysis, we used the VIX level, term spread, credit spread, and interest rate level as regime indicators.[17] The results are not consistent with a time-varying

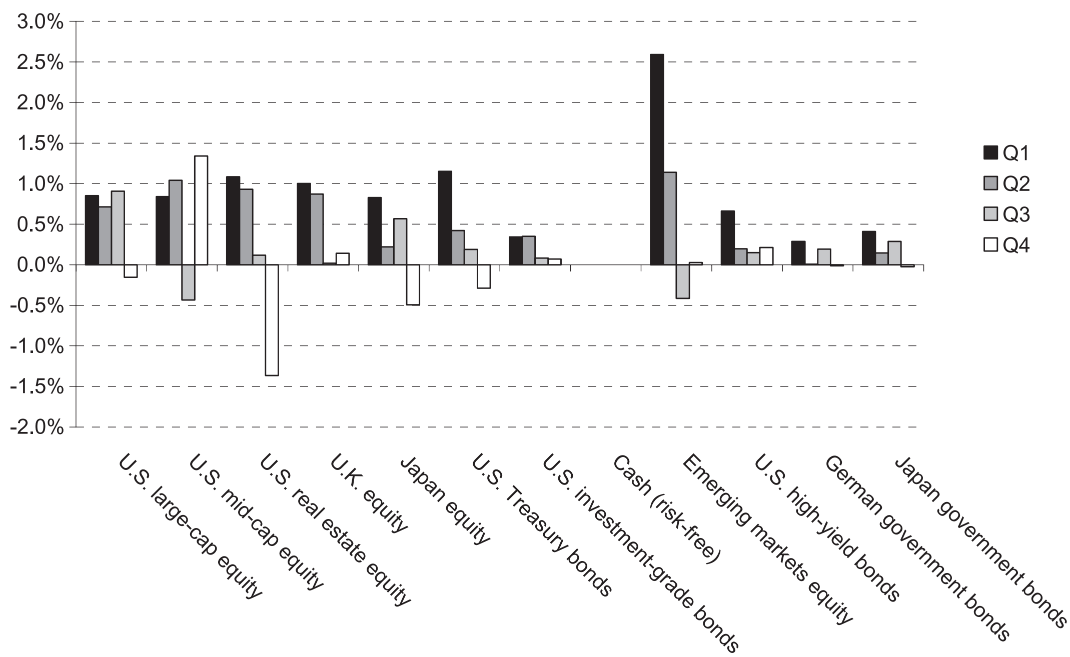
EXHIBIT 10

Results Using Volatility-Adjusted Returns for Each Asset Class, February 1986 to September 2007

	Q1	Q2	Q3	Q4		Q1-Q4
1-Month Momentum						
Mean return	7.3%	6.4%	2.1%	–0.1%	Outperformance	7.4%
Standard deviation	7.5%	7.1%	6.1%	8.0%	Tracking error	9.1%
Sharpe ratio	0.98	0.89	0.34	0.01	Information ratio	0.82
					T-statistic	3.79***
12-1 Month Momentum						
Mean return	5.6%	5.7%	3.6%	0.7%	Outperformance	5.0%
Standard deviation	8.4%	6.1%	6.6%	7.5%	Tracking error	9.6%
Sharpe ratio	0.67	0.94	0.54	0.09	Information ratio	0.52
					T-statistic	2.40**
Valuation						
Mean return	6.6%	4.2%	2.5%	2.3%	Outperformance	4.4%
Standard deviation	7.3%	6.2%	7.0%	8.3%	Tracking error	9.5%
Sharpe ratio	0.92	0.68	0.36	0.27	Information ratio	0.46
					T-statistic	2.15**
Combination Strategy						
Mean return	8.4%	4.8%	3.2%	–0.8%	Outperformance	9.2%
Standard deviation	6.5%	7.4%	7.3%	7.1%	Tracking error	7.8%
Sharpe ratio	1.29	0.65	0.43	–0.11	Information ratio	1.18
					T-statistic	5.50***

EXHIBIT 11

Average Monthly Excess Return Conditional on Quintile Classification of Combined Strategy



risk explanation, because alpha spreads are positive in all states-of-the-world. For example, the valuation premium does not depend on the VIX level or term spread, although it does seem to be higher during periods with low interest rates and low credit spreads, such as over the 2003–2006 period. Neither of the momentum strategies show a clear link to economic states-of-the-world. For the combined strategy, we do not find an obvious relation between the economic environment and the returns of the GTCAA strategy.

If all the explanations discussed thus far are inadequate, we are left to consider the possibility that our results may represent a new asset pricing puzzle, which challenges market efficiency and market equilibrium. Unfortunately, the concept of market efficiency in the context of GTAA is not well defined, because no generally accepted asset pricing model applies to the wide variety of asset classes that are covered in our study. Interestingly, the momentum and value effects which we observe across different asset classes are conceptually similar to the effects that have previously been documented within asset classes or at the level of individual asset classes, and for which behavioral explanations have been put forward. This raises the question of whether the momentum and value effects which we observe across asset classes might also be capturing inefficiencies caused by behavioral effects, and thus posing a challenge to market efficiency. Inefficiencies at the asset class level might be caused by too little "smart money" available to actively arbitrage inefficiencies away as soon as they occur. We provide two lines of reasoning which support this hypothesis.

First, many investors may want to refrain from an aggressive, broad tactical cross-asset allocation simply because they perceive it to be too challenging. As noted earlier, we lack a solid theoretical framework for pricing the heterogeneous set of asset classes covered in our analysis, so that a large degree of uncertainty surrounds the fair valuation of these asset classes. For example, even though we find empirically that our GTCAA valuation strategy is effective, we do not believe that, in equilibrium, every asset ought to be valued according to the simple valuation measures used in that particular strategy.

Second, most professional market participants, such as fund managers and analysts, focus on allocation and security selection within a certain asset class. For example, a high-yield bond manager tends to focus on picking the best high-yield bonds and is usually not concerned about the attractiveness of high-yield bonds as an asset class compared to, for example, REITs. Instead, allocation decisions across asset classes tend to be made primarily by end-investors, such as pension fund boards and individuals, whose behavior may be driven primarily by factors, such as

- long-term considerations (e.g., adhering to a strategic mix which follows from an asset/liability management study);
- fixed allocation mechanisms (e.g., the use of a prespecified asset allocation mix for cash inflows, such as 401K plan contributions, throughout a year)
- herding behavior (i.e., not wanting to deviate too much from the peer group);
- recent performance of an asset class, because considerably more money tends to flow into "hot" asset classes that have recently exhibited strong performance than into asset classes with mediocre or disappointing returns.

Following this reasoning, it is not hard to imagine that mispricing effects may arise at the asset class level. Furthermore, this also suggests that these effects are likely to persist going forward, at least until more smart money becomes available to actively arbitrage away this opportunity for alpha.

Hedge funds constitute a natural source of smart money, as these funds have the flexibility to take advantage

EXHIBIT 12

GTCAA Q1-Q4 Strategy Returns in Different Regimes, February 1986 to September 2007

	VIX		Term Spread		Credit Spread		Interest Rate	
	Low	High	Low	High	Low	High	Low	High
1-Month Momentum	8.9%	6.0%	5.2%	8.2%	6.8%	6.8%	9.1%	4.7%
12-1 Month Momentum	9.8%	7.1%	6.6%	8.6%	9.6%	6.3%	7.1%	9.4%
Valuation	9.0%	7.2%	6.1%	9.8%	1.1%	12.4%	14.2%	3.5%
Combination Strategy	13.9%	10.8%	10.7%	12.9%	9.8%	13.4%	15.7%	8.9%

EXHIBIT 13

T-Statistics of Regressions of Credit Suisse/Tremont Hedge Fund Index Returns on GTCAA Q1-Q4 Strategy Returns, January 1994 to September 2007

Multi-Factor Regression	Momentum 1M	Momentum 12-1M	Valuation	Single-Factor Regression	Combination Strategy
Hedge funds	1.2	**2.7**	–2.4	Hedge funds	–1.5
Convertible arbitrage	–0.6	0.2	0.0	Convertible arbitrage	–0.4
Dedicated short bias	–0.4	–0.6	0.0	Dedicated short bias	–0.7
Distressed	0.7	–0.9	–0.7	Distressed	0.4
Emerging markets	1.8	–0.6	–2.9	Emerging markets	–1.8
Equity market neutral	0.5	–0.4	–1.0	Equity market neutral	–1.1
Event driven	0.8	–0.7	–0.9	Event driven	0.1
Event driven multi-strategy	0.7	–0.5	–1.2	Event driven multi-strategy	–0.4
Fixed-income arbitrage	–0.4	1.5	–0.7	Fixed income arbitrage	–1.4
Global macro	1.6	**2.7**	–2.3	Global macro	–1.6
Long/short equity	0.5	**3.1**	–2.0	Long/short equity	–0.7
Managed futures	**2.2**	**5.4**	1.2	Managed futures	**2.7**
Multi-strategy	–0.1	**3.1**	**3.1**	Multi-strategy	**2.8**
Risk arbitrage	0.2	–1.7	0.6	Risk arbitrage	0.9

Note: Positive relations that are significant at the 5% level are highlighted in bold.

of alpha that is ignored by many traditional managers. We would expect a priori that managed futures and global macro hedge funds are particularly good candidates for engaging in GTCAA-type strategies. In order to investigate whether hedge funds are indeed trying to exploit GTCAA alphas, we regress the GTCAA strategy returns on hedge fund returns. The results, shown in Exhibit 13, provide a mixed picture.

We observe that the returns of certain hedge funds do indeed appear to be related to our GTCAA strategies. However, this result is mainly driven by exposure to the GTCAA 12-1 month momentum strategy, which is strongly related to momentum at the stock level, such as the UMD effect. The GTCAA 1-month momentum and value strategies appear to be considerably less popular among hedge funds, as we find only one positive and significant *t*-statistic for each of these strategies. For global macro, one of the most likely smart money candidates, we find a significantly negative relation to our GTCAA valuation strategy. This may be due to the fact that the horizon required for this strategy is too long for funds that are strongly focused on short-term performance. More negative exposures are found for other hedge fund styles, and we even find a negative relation between the combined strategy and the aggregate Credit Suisse/Tremont Hedge Fund Index. Thus, we conclude that although some hedge funds may be trying to exploit some of the cross-market allocation alphas documented in this article, the overall results do not indicate this is occurring on the large scale needed to arbitrage away all these effects.

CONCLUSION

We find statistically and economically significant return premiums between 7% and 8% for 1-month momentum, 12-1 month momentum, and value GTCAA strategies over the 1986–2007 period. For a GTCAA strategy based on a simple combination of momentum and value factors, we find an alpha of 12% a year. Our findings are not only practically, but also theoretically, relevant as they show that effects previously documented to exist *within* asset classes are also observed *across* entire asset classes. However, we are not simply capturing known effects in a new way, because the combined strategy returns, in particular, remain strong after adjusting for implicit loadings on, for example, the Fama–French value and Carhart momentum factors. Thus, although similar in spirit, the cross-asset effects do constitute different return irregularities. This adds yet another puzzle to the field of empirical asset pricing and a challenge to market efficiency.

We have provided several arguments against risk-based explanations for our findings. We argue instead that financial markets may be macro inefficient due to insufficient smart money available to arbitrage away mispricing effects that may arise due to behavioral effects. Certain types of hedge funds might be expected to represent this smart money and thus be likely candidates to take advantage of the cross-asset allocation alphas in practice. Although we find some evidence which seems to be consistent with this, other evidence points to behavior which is contrary to our GTCAA strategies.

Our results may be extended in several ways. One direction for follow-up research would be to expand the number of asset classes covered by the strategy; by adding for example, asset classes which now have only a short data history (e.g., emerging markets debt and hedge funds); which are more difficult to model, particularly with regard to valuation (e.g., commodities and currencies); or which are less liquid and/or lack market prices (e.g., direct real estate and private equity). A second way to extend the research would be to analyze more potential predictor variables. Variables that are not asset class–specific may be particularly interesting in this regard. For example, Jensen, Mercer and Johnson [1996, 2002] related monetary conditions to future stock returns and future commodity returns. Calendar and seasonal indicators, such as January or winter/summer effects, might be useful as well, or macroeconomic indicators, such as consumer and producer confidence, interest rate changes, oil price movements, and so forth. A third possible extension of our research might be some form of portfolio optimization to try to further improve risk-adjusted returns. For example, the simple ranking method we use ignores correlations between the selected assets and thus may be suboptimal. By expanding the number of assets, by finding new alpha factors, and/or by more advanced portfolio construction, the case for global tactical cross-asset allocation might be further strengthened.

ENDNOTES

The authors thank Thierry Post, Laurens Swinkels, and an anonymous referee for valuable comments on an earlier version of this article, and Xiaomin Pang for research assistance.

[1]Goldman Sachs is an example of a well-known GTAA provider using this approach. See, for example, http://www2.goldmansachs.com/client_services/asset_management/institutional/pdf/global_tactical.pdf.

[2]We did not attempt to test for a GTCAA size effect. A priori we do not expect to find a size effect across asset classes, as the size of an asset class is not a straight reflection of the economic size of the underlying securities, but also depends on the breadth of that asset class (i.e., the number of different securities).

[3]In this way, we avoid a universe that is basically an equity country allocation universe (for which a lot of research is already available) plus a few other assets.

[4]Today markets are more liquid and more instruments are available than in the earlier part of the sample. For example, in addition to futures, OTC swaps or ETFs may constitute alternative instruments for efficiently gaining exposure during the latter part of the sample.

[5]By taking into account the covariance matrix of asset returns, the full potential of TAA can be unlocked. We partly address this issue in the sensitivity analysis when we use volatility adjusted bet sizes instead of equal bet sizes.

[6]The specific strategic asset allocation of an investor is ignored in our analysis, based on the finding in Lee [2000] that when tactical asset allocation is approached from a portable alpha perspective, the optimal tactical bets are entirely independent of the underlying benchmark portfolio.

[7]As earnings yield data is not available for U.S. real estate equity, we use dividend yield data for this asset class. This is actually not a bad approximation, as REITs are legally obliged to distribute at least 90% of their income as dividends.

[8]The price we pay to obtain a more reasonable value strategy without structural biases is the introduction of a look-ahead bias, because in the past an investor might have considered certain alternative adjustment levels to be more appropriate. However, we also find strong results (not reported) for an alternative valuation strategy which is free of look-ahead bias. This approach consists of normalizing the valuation level of an asset class by adjusting for its own historical average. Disadvantages of this alternative approach are that it is more data intensive (as a result, the sample period is shortened) and it introduces another kind of ambiguity (i.e., which lookback period, different adjustments for similar assets, and so forth).

[9]In order to avoid occasional ties, we give a 25.01% weight to the 12-1 month momentum variable. We give slightly more weight to the slower momentum factor in order to limit turnover.

[10]The same is actually true for each of the three underlying strategies.

[11]The data for this analysis was taken from the Kenneth French website.

[12]This finding differs from the cross-market momentum results of Pirrong [2005], who also performed a four-factor correction which did not significantly affect the alpha. This might be attributed to differences in the universe of assets and/or sample period.

[13]In practice, transaction costs might be reduced significantly by applying more advanced buy and sell rules. For example, an asset which drops from rank 3 (out of 12) to 4 falls out of the top quartile and is thus replaced in the Q1-Q4 portfolio. However, given the fact that the change in rank is only one notch and given that the second-quartile portfolio also outperforms, it may in fact be more attractive on an after-cost basis to hold on to the position in such an asset.

[14]Except the risk-free asset, because this has zero volatility.

[15]Note that for some asset classes there is insufficient return history for the initial years of the sample. In such cases we use volatilities calculated over the first 60 months of the series instead. This introduces a slight look-ahead bias, but in our view not a serious one as volatility is used only as a scaling factor.

[16]Further analysis reveals that 12-1 month momentum is the main culprit for the weak performance of the strategy on U.S. mid-cap equity.

[17]The data are obtained from the St. Louis Federal Reserve. The VIX is the implied volatility on 1-month S&P 100/500 index options, the term spread is defined as the difference between 10-year and 1-year U.S. Treasury yields, the credit spread is the difference between Baa and Aaa corporate bond yields, and the interest rate level is the 30-day T-bill rate.

REFERENCES

Chan, K., A. Hameed, and W. Tong. "Profitability of Momentum Strategies in the International Equity Markets." *Journal of Financial and Quantitative Analysis*, Vol. 35, No. 2 (2000), pp. 153–172.

Fama, E.F., and R.R. Bliss. "The Information in Long-Maturity Forward Rates." *American Economic Review*, 77 (1987), pp. 680–692.

Fama, E.F., and K.R. French. "Business Conditions and Expected Returns on Stocks and Bonds." *Journal of Financial Economics*, 25 (1989), pp. 23–49.

——. "Multifactor Explanations of Asset Pricing Anomalies." *Journal of Finance*, Vol. 51, No. 1 (1996), pp. 55–84.

——. "Value versus Growth: The International Evidence." *Journal of Finance*, Vol. 53, No. 6 (1998), pp. 1975–1999.

Froot, K.A., and R.H. Thaler. "Foreign Exchange." *Journal of Economic Perspectives*, Vol. 4, No. 3 (Summer 1990), pp. 179–192.

Hodrick, R.J. *The Empirical Evidence on the Efficiency of Forward and Futures Foreign Exchange Markets*. London: Harwood, 1987.

Ilmanen, A. "Time-Varying Expected Bond Returns in International Bond Markets." *Journal of Finance*, Vol. 50, No. 2 (1995), pp. 481–506.

Jagadeesh, N. "Evidence of Predictable Behavior of Security Returns." *Journal of Finance,* Vol. 45, No. 3 (1990), pp. 881–898.

Jagadeesh, N., and S. Titman. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *Journal of Finance*, Vol. 48, No. 3 (1993), pp. 65–91.

Jensen, G.R., J.M. Mercer, and R.R. Johnson. "Business Conditions, Monetary Policy, and Expected Security Return." *Journal of Financial Economics*, Vol. 40, No. 2 (1996), pp. 213–237.

——. "Tactical Asset Allocation and Commodity Futures." *Journal of Portfolio Management*, Vol. 25, No. 4 (2002), pp. 100–111.

Lee, W. *Theory and Methodology of Tactical Asset Allocation*. New York, N.Y.: John Wiley and Sons, 2000.

Moskowitz, T.J., and M. Grinblatt. "Do Industries Explain Momentum?" *Journal of Finance*, Vol. 54, No. 4 (1999), pp. 1249–1290.

Pirrong, C. "Momentum in Futures Markets." Working paper, SSRN No. 671841, 2005.

Richards, A.J. "Comovements in National Stock Market Returns: Evidence of Predictability, But Not Cointegration." *Journal of Monetary Economics*, 36 (1995), pp. 631–654.

——. "Winner–Loser Reversals in National Stock Market Indices: Can They Be Explained?" *Journal of Finance*, 52 (1997), pp. 2129–2144.

Rouwenhorst, K.G. "International Momentum Strategies." *Journal of Finance*, Vol. 53, No. 1 (1998), pp. 267–284.

Sharpe, W.F. "Integrated Asset Allocation." *Financial Analysts Journal* (September/October 1987), pp. 25–32.