Multi-Asset Sentiment and Institutional Investor Behavior: *A Cross-Asset Perspective*

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Greater financial integration and similar central bank policy initiatives in major developed markets have led to an increase in cross-asset return correlations, highlighting the interest in broad measures of market-wide sentiment. Using an extensive array of institutional behavioral data across asset classes from State Street Associates, we find evidence that suggests market-wide sentiment varies with, and can even be forecasted by, broad aggregates across many indicators of institutional investor flows.

Previous research has found that many specific flow measures can be helpful in explaining current and future returns in those same assets. Here, however, we examine predictions across assets and asset classes. For example, we see not only that equity inflows can help explain current and future equity returns, but also that there is additional power in including bond outflows in explaining equity returns. This suggests that market-wide sentiment—a risk-on/off perspective—might best be defined and observed by a specific cross-sectional pattern of flows into and out of a wide group of assets. Risk-on attitudes might most sensibly be expected to be associated with purchases of riskier equities and bonds—emerging market equities and debt, international stocks, growth stocks, high yield bonds, and so on—and sales of safer asset classes—high-dividend stocks, utilities, investment grade and developed-country sovereign debt, and so on. If these flow patterns act as observable proxies for positive sentiment, then current and even future market-wide returns should be reliably positive when they appear.

Indeed, because these flow measures display surprisingly consistent properties across asset classes, we expect that aggregates of these multi-asset flows display these properties more strongly. For example, if asset flows are persistent and positively correlated with own-asset returns, then we should find multi-asset class aggregations to be even more strongly persistent and positively correlated with aggregate asset returns.

The large number and wide breadth across assets of these institutional flow measures encourages aggregation into a more manageable set of elements. To this end, we condense this broad information set into what we call a Behavioral Risk Scorecard (BRS), a concise measure of behavior that captures trading sentiment using State Street Associates' dashboard of flow indicators.

INSTITUTIONAL INVESTOR BEHAVIOR

State Street Associates produces a wide dashboard of behavioral indicators, based on the aggregated activities of institutional investors. These investors represent more than $25 trillion in assets across tens of thousands of portfolios and are broadly representative of the universe of institutional investors. Although the group is diverse, their behaviors are actually more similar to one another than to those against whom they trade: predominantly corporate and retail investors, and more recently the Fed, in bonds and mortgages.

Similarities between these institutional portfolios and strategies—and differences between them and the rest of the market—make aggregate measures of their behavior interesting. Without these similarities, information from a collection of investors would be random, and so would have little to say about prices, flows, or holdings. But the similarities are indeed strong, and so we find that when institutional investors are in the market buying—and therefore others, necessarily, are selling to them—prices are rising. Indeed, we observe this relationship between contemporaneous institutional investor flow and return across virtually all assets and asset classes, and consistently though time. Thus, institutional investors tend to be the more motivated traders, demanding immediacy from the marketplace. The fact that this pattern is so persistent across asset classes and over time means that motivated trading is shared more strongly across institutional portfolios than it is across retail and corporate investors. The presence of such basic common attributes suggests that aggregate derived measures of institutional investor behavior—even obvious ones, such as flows, holdings, agreement levels, and so on—will be quite different from the market overall and therefore potentially informative about the future.

So what can measures of aggregate institutional behavior tell us about market conditions? The list is surprisingly long. There are many measures of the aggregate behavior of these institutional investors to choose among—thousands each day, in fact. Flows, benchmark holdings, over- and under-weights, agreement levels, risk appetite, and PNL measures all cut across major asset classes and currencies, and are stratified in many ways, including by country, industry, style, a wide variety of company attributes, credit, liquidity, and so on. Flow is an important behavioral concept, telling us what institutional investors are buying.

With all this detailed behavioral information comes the desire to summarize its most important themes. As with a presidential election, there are many interesting details describing voting trends within the electorate. However, the first thing a voter wants to know about an election is the outcome: "Who won?" In some sense, that is the objective of this article: to introduce a single summary measure of behavior that can gauge relatively well investors' appetite for risk, using our very broad dashboard of indicators. Who is this day's winner in the daily runoff between risk-on and risk-off?

To do this, we focus on a simple scorecard approach, using only flow measures. For the purposes of this measure, this means ignoring all the other behavioral concepts, such as holdings, agreement, breakeven price, and so on, in order to focus solely on flow. Even with this restrictive set, however, we are looking at thousands of flow series across every industry, country, currency, and style for a large spectrum of more than 10,000 global stocks. So we begin with a foreshortened universe of 121 flow measures, summarizing major asset-class groupings. We also distill this rather large aggregate down to a smaller aggregate across an even more manageable set of 22 flow measures and composites. We then look at the properties of these scorecard aggregations, interpreting them as overall measures of risk appetite.

Our first step is to classify each flow indicator as a "risk-on" or "risk-off" measure, based on simple intuition. For example, emerging-market equity flows would be considered a "risk-on" measure, insofar as those markets are generally considered by investors to be relatively risky. Flows into Treasury bonds, which by contrast are perceived by investors as a safe-haven asset, are "risk-off." These opposite risk assignments are corroborated when we see that, perhaps not surprisingly, T-bond and EM equity flows are negatively correlated.

Besides these more obvious black and white risk assignments, some asset-class flows seem grey. We try to classify these according to what we think of as a consensus interpretation. However, our results are not very sensitive to how these relatively few grey indicators are assigned. Each indicator is assigned to be risk-on or risk-off. Given that sign, there is no effect of magnitude. This keeps things simple and focused on the cross-sectional breadth of flow, rather than on individual components and their magnitudes.

LITERATURE REVIEW

In finance, market sentiment—the aggregate of market expectations and investor behavior—can be a strong determinant of asset returns and has piqued the interest of practitioners and academics alike. Indeed, previous research has shown that levels of historical stock volatility are too high to be justified by fundamentals alone (LeRoy and Porter [1981]; Shiller [1981]; Campbell and Shiller [1988]), suggesting that discount rates are determined by intrinsic risk, as well as by the perceptions of risk, or investors' risk sentiment. Furthermore, Barberis et al. [1998] and Bordalo et al. [2012] present parsimonious models of investor sentiment based on psychological evidence, suggesting that under-reaction and overreaction in stock markets can in fact be exploited to generate excess return, without bearing additional risk.

Over the last decade, the focus has shifted from establishing that sentiment drives asset returns to identifying more appropriate measures that capture sentiment. Using proxies, including the closed-end fund discount, NYSE share turnover, the IPO market, the share of equity issues in total equity and debt issues, and the dividend premium as inputs, Baker and Wurgler [2006, 2007] construct a stock-sentiment index based on principal component analysis, providing further evidence that aggregate sentiment affects cross-sectional stock prices. Bandopadhyaya and Jones [2008] study two of the commonly watched market sentiment indices: the put-call ratio (PCR) and VIX. They find that the PCR can better explain variations in the S&P 500 index, after controlling for economic factors. Other sentiment indices based on surveys, such as the University of Michigan consumer sentiment index, have been shown to contain predictive power (Charoenrook [2005]) and can be used in dynamic asset allocation (Basu et al. [2006]).

The major challenge in capturing market sentiment is that generally it is only measurable with a degree of accuracy after the fact, so faster-moving sentiment measures may not be helpful for predictive purposes, given the speed at which information is incorporated into prices. However, it is widely known that institutional investors, as a whole, exhibit trading behavior that is more persistent through time (Froot et al. [2001]; Froot and Donohue, [2002]). Using a representative sample of institutional investors' trades and holdings, Froot and O'Connell [2003] decompose the demand for equities into two components, one based on fundamentals and the other based on investor confidence or risk tolerance, to disaggregate their respective effects on global prices. The analysis shows that their measure of risk tolerance, or investor confidence, explains a substantial amount of variation in portfolio holdings and also has predictive properties.

As financial markets become increasingly integrated, investors are exploring cross-asset interaction, in search of additional sources of alpha. Indeed, analysis by Friewald et al. [forthcoming] shows that a firm's equity returns and Sharpe ratio increase with estimated credit risk premia, a finding that is consistent with Merton's structural model [1974], suggesting that firms' risk premia in equity and credit markets are related. Research by Erturk and Nejadmaleyeri [2012] indicates that short-selling activity in the equity markets conveys negative information about future bond prices, finding that when short interest rises, the credit spread increases. Nayak [2010], using a composite constructed by Baker and Wurgler [2006] that is based on stock-market information, finds that credit yield spreads co-vary with investor sentiment. More recently, Lee [2012] studies the risk-on/risk-off market theme that has prevailed since the 2008–2009 financial crisis, in which investors indiscriminately buy or sell risky assets, depending on risk appetite. Furthermore, recent work by Maggiori [2013] shows that the U.S. dollar is a safe haven to which investors flock in times of crisis, earning a safety premium compared to a basket of currencies. To capture the systemic risk across financial markets, Kritzman and Li [2010] constructed a market-turbulence index, using price data across multiple asset classes, including U.S. and non-U.S. equities, U.S. bonds and non-U.S. bonds, commodities, and U.S. real estate. These studies all emphasize the importance of monitoring investor risk sentiment from a multi-asset class perspective.

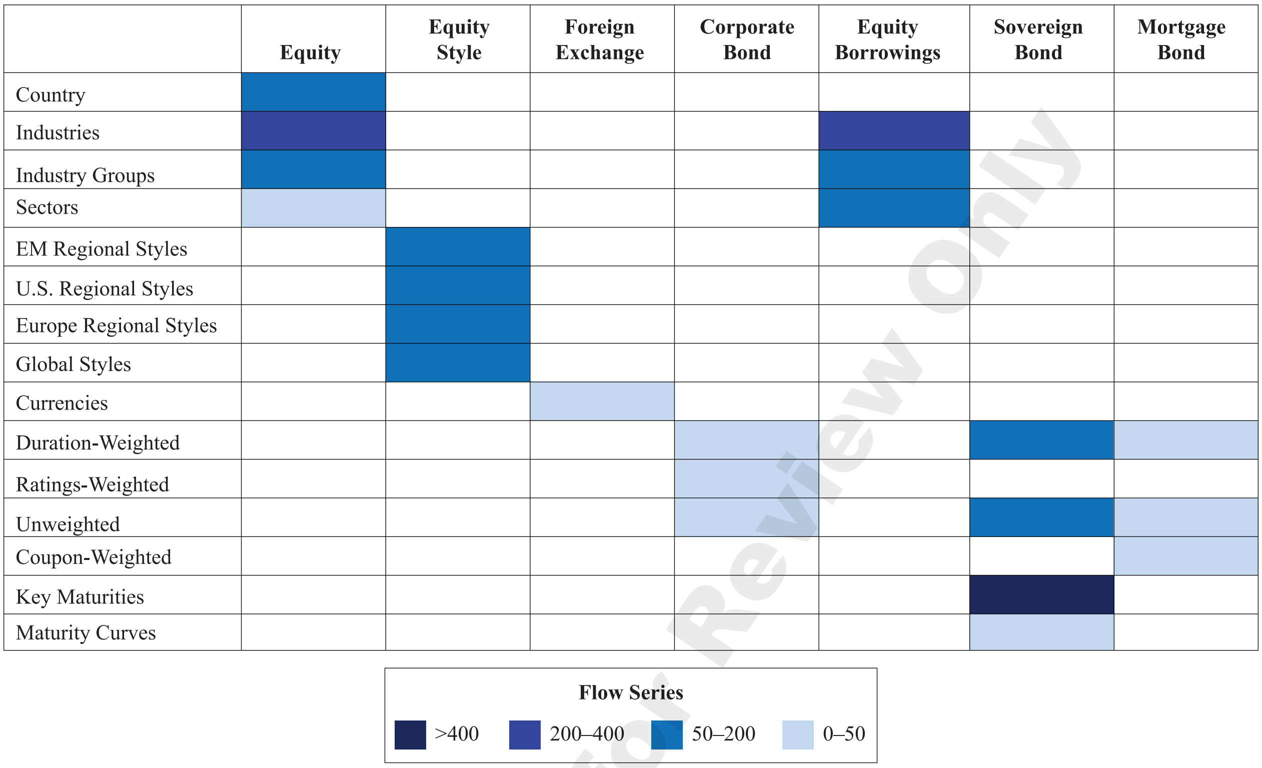
In this article, we expand on the literature by presenting a simple and intuitive methodology to build a multi-asset sentiment index, based on a scorecard approach to both measure multi-asset sentiment and also drill down to specific asset-class drivers. Another advantage associated with this framework that it can easily incorporate additional signals.

DATA/SCORECARD CONSTRUCTION

To construct aggregate measures of trading sentiment, we use indicators from State Street Associates' comprehensive suite of daily flows (Exhibit 1). We define an aggregate measure from this subset using a three-step process. First, for each constituent of the 121 flow-series, we assign a yes/no/maybe dummy based on our intuition of the risk nature of the variable: Does flow into that asset represent risk-on or risk-off sentiment?

Exhibit 1

State Street Associates' Metrics of Trading Sentiment



Source: State Street Associates.

In the exhibits, green indicates a risk-seeking group of assets, red indicates risk-averse assets, and yellow indicates a lack of conviction for either.

We next compute the flows for each element in each asset class. Here, flow is a 20-day moving average of that flow indicator's values, reported as a conditional percentile over the last five years of data.[1] Once again, the final value of flow is just a dummy. At any given time for an indicator, its value is +1 if that indicator flow is positive, and −1 if that indicator flow is negative. Finally, we take the product of the two; i.e., we multiply dummy by flow. This ensures that the flows are aligned in the same direction of risk appetite. The resulting scorecard series for each indicator can therefore only have values of +1, 0, and −1.

Behind much of the increase in cross-asset correlation is a single factor that describes an increasing amount of risk. As always, it is hard to identify news that supports the magnitude and pervasiveness of this source of co-movement. Behavioral phenomena, such as investor sentiment, can help fill in these gaps. Furthermore, given the pervasiveness of this common source of excess co-movement, one can gain insights into aggregate sentiment by measuring behavior across as many asset classes as possible. We therefore expect our cross-asset measure of sentiment to be useful in timing aggregate risk. To quantify aggregate sentiment, we use three scores: one at the level of the individual indicator, a second at the level of the asset class, and a third across asset classes. We call the third aggregation our BRS multi-asset score. For BRS, green indicates risk-seeking flows and red indicates aggregate risk aversion. In order to generate the BRS multi-asset score, we sum across the chosen scorecard series, as previously calculated, on a weekly basis.

We also distill the number of indicators to just 22, in order to more readily monitor the individual components and aggregate scores. These are the indicators that seem to us most intuitively reflective of risk-on or risk-off behavior. We find this smaller subset captures the broader movement of the larger 121-indicator set. Indeed, both series tend to move with asset risk, and experience large declines in sentiment during crises, relative to other periods. Exhibit 2 lists the 22-element series components. As above, the 22 elements cover four major asset classes and the multi-asset risk-on/risk-off factors. The "+/−" signs highlight elements that move positively/negatively with risk appetite.

Aggregate multi-asset sentiment, as well as asset class sentiment, is generated in a weekly snapshot, shown in Exhibit 3. The scorecard highlights investor attitude towards risk, with green and red signaling risk-seeking and risk-averse behavior, respectively. Here, color intensity also captures the magnitude of the flow, with darker colors highlighting the extremes in the top or bottom quartiles.

Equity Flows

We chose among many equity flow indicators using intuition to decide whether the flows move with (or against) risk-on versus risk-off environments. We chose six equity indicators. The first is developed-market aggregate equity flows, a capitalization-weighted aggregate of 23 developed-market country equity flows. The second is the analogous emerging-market aggregate, which includes 21 emerging-market country equity flows. The third element is the cyclical-minus-defensive global sector flow series. Cyclicals include the materials, industrials, consumer discretionary, and information technology sectors, under the rationale that these sectors generally co-vary most with risk appetite. By contrast, defensive sectors include consumer staples, health care, telecom, and utilities. Fourth, we include cyclical minus defensive borrowings (a contrarian indicator), using data from global equity borrowings. These describe short-selling demand for individual sectors. Finally, we track equity style flow indicator slopes, which measure the strength with which flows into equities increase, on average, with the style or attribute in question—i.e., value. Given the bond-like quality of equities that pay high dividends, the global dividend yield style slope tends to act like Treasury bond returns and flows (to the extent that the Fed does not drive the latter).

Fixed-Income Flows

In the fixed-income space, we monitor the flow differential between two-year and ten-year U.S. sovereign bonds. Higher relative flows into two-year Treasuries portend a steeper yield curve and positive growth expectations. We also monitor duration-weighted sovereign bond flows into the core developed markets—the U.S., U.K., and Germany—weighted by outstanding debt. Flows into this group imply a flight to quality by institutional investors. In addition, we track flows into the top three sovereign bond markets ranked by 10-year rates, high yield minus investment grade U.S. duration-weighted corporate bond flows, and aggregate sovereign bond flows into emerging markets. These three series indicate risk-seeking behavior.

Currencies

In the foreign-exchange markets, we sort currencies based on three-month interest rates, in order to track currency flows into the top five high-yield currencies (risk-seeking) and the top five funding currencies (risk averse). In addition, we track aggregate emerging-market currency flows and U.S. dollar flows; higher inflows into the latter indicate a flight to safety.

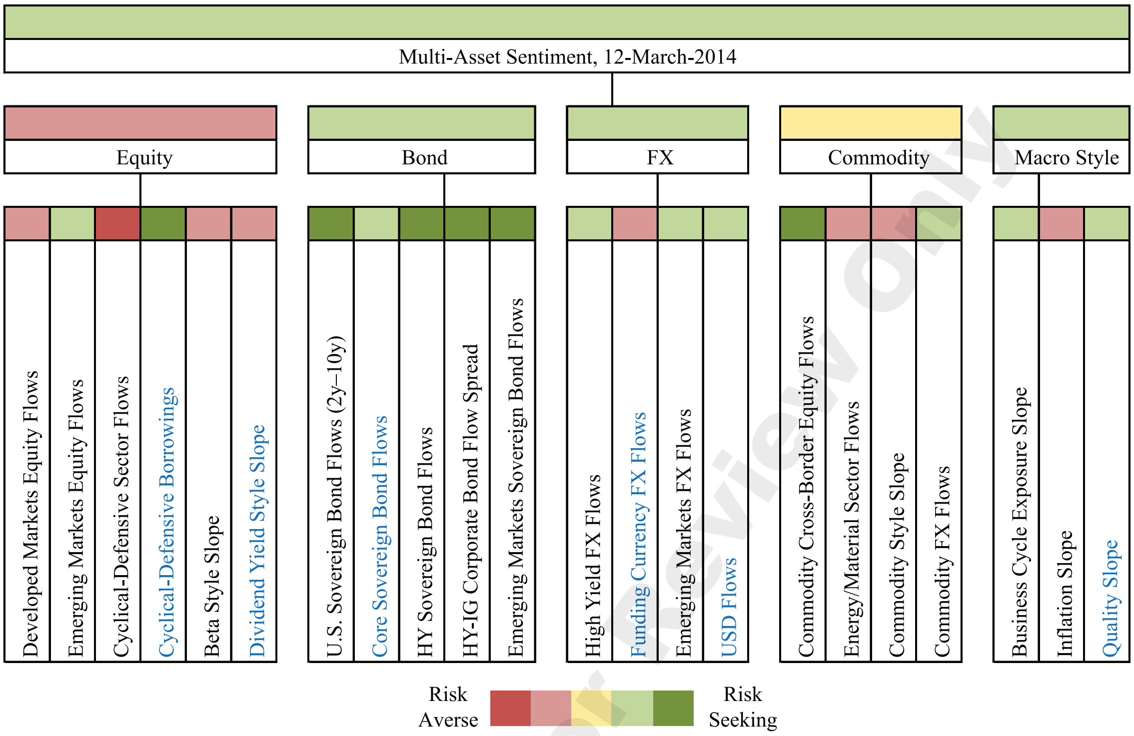
EXHIBIT 2
Behavioral Risk Scorecard, 22 Series

Equity	**Currencies**
Developed Market Equity Flows (+)	High Yield FX Flows (+)
Emerging Market Equity Flows (+)	Funding Currency Flows (–)
Cyclical-Defensive Sector Flows (+)	Emerging Market FX Flows (+)
Cyclical-Defensive Equity Borrowings (–)	USD Flows (–)
Beta Style Slope (+)	**Commodities**
Dividend Yield Style Slope (–)	Commodity Cross-border Equity Flows (+)
	Energy/Materials Sector Flows (+)
Fixed Income	Commodity Style Slope (+)
	Commodity FX Flows (+)
U.S. Sovereign Bond Flows (2y–10y) (+)	**Macro Style**
Core Sovereign Bond Flows (–)	Business Cycle Exposure Slope (+)
HY Sovereign Bond Flows (+)	Inflation Slope (+)
HY-IG Corporate Bond Flows (+)	Quality Slope (–)
Emerging Market Sovereign Bond Flows (+)	

Source: State Street Associates.

Exhibit 3

Behavioral Risk Scorecard, Weekly Snapshot



Source: State Street Associates.

Commodities and Macro Style

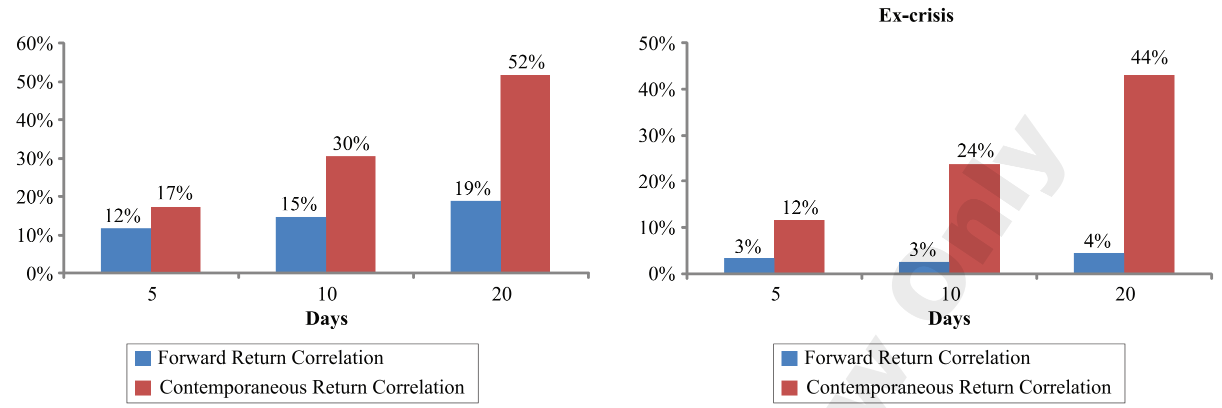
For commodities, we monitor four flow series that serve as proxies for commodity demand across equity and currency markets: a market-cap-weighted aggregate of the cross-border equity flows into 14 commodity-based exporting countries; market-cap-weighted global sector flows into energy and materials; the commodity style slope, which measures equity flows into stocks correlated with commodity returns as measured by the S&P GSCI Total Return index; and an aggregate commodity currency flow series. Finally, for the macro style subset, we monitor several additional equity style slopes: business-cycle exposure, inflation, and quality. The quality slope measures equity flows into stocks with relatively high return-on-equity ratios, which are generally considered safer equity securities.

As mentioned before, the scorecard has three levels: the indicator level, which highlights investor demand for each of the 22 elements; the asset class level, which rolls up sentiment from the relevant indicators within each asset class; and the multi-asset-level, which aggregates sentiment across all 22 elements. The asset and multi-asset-levels are also color coded (see Exhibit 3), though here we use asset-level scores as the color driver. We assign a +1 to base elements with positive dummy values (green), −1 to those with negative dummy values (red), and sum for each asset class. For the multi-asset score, we simply add scores across all the asset classes. Aggregates with scores above zero are shaded green; those below zero are shaded red.

Our scores are based on five-year conditional percentile transformations of each underlying flow indicator. A category (equity, bond, FX, commodities, or macro style) is green if the conditional percentile (which essentially measures inflows and outflows) is greater than 50%, red if the conditional percentile is less than 50%, and yellow if the conditional percentile is 50% (i.e., a score of zero). Note that series with blue text represent flows that correlate negatively with risk.

EXHIBIT 4

Multi-Asset Score, Correlations with Risky Asset Return Index



Source: State Street Associates, Thomson Datastream.

Properties

Across asset classes, flow indicators exhibit consistent properties, including persistence, positive price impact, and momentum-like return predictability. For our multi-asset measure to be informative, it's important that these properties also translate into the aggregate measures. Therefore, we measure contemporaneous and forward return correlations with our BRS multi-asset score. In Exhibit 4, we use an equally-weighted risky asset return index that includes the MSCI ACWI, the Barclays U.S. High Yield total return index, the JP Morgan ELMI+ index, and the S&P GSCI total return index. The results show consistent price impact (contemporaneous return correlation) across the one-week, two-week, and one-month horizons. Furthermore, return predictability is evident. Importantly, results hold when we exclude the crisis; however, the magnitude of the correlations drops.

We also separately measure the price impact and return predictability of our aggregate multi-asset score for each of the four risky asset return indices. We compute individual asset-level scores using their respective asset class return series (Exhibit 5). Although asset-level scores reveal consistent price impact and return predictability, on average, our multi-asset score has greater price impact and return predictability.

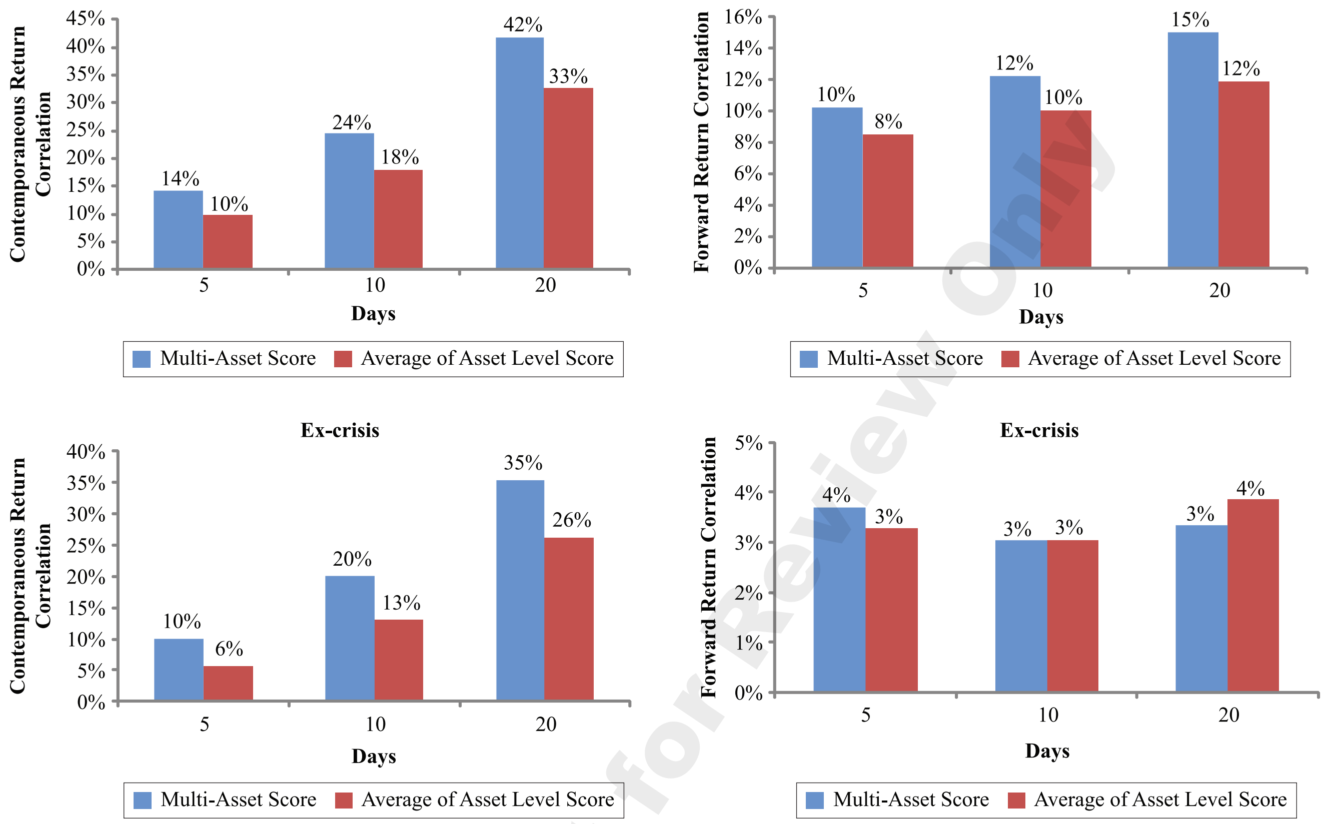
Proof of Principle Backtests

Given that the BRS multi-asset score gauges risk sentiment, we now test how the aggregate score performs in timing asset allocation and asset class-specific risk. There are three measures derived from the BRS multi-asset score that we find useful to apply. Each tells us something slightly different about the risk environment (Exhibit 6). First, we use the sign of the BRS multi-asset score. This represents our estimate of the sign of the aggregate sentiment underlying the general risk environment, or attitude towards risk. We designate the sign by "S," and use the notation "$S > 0$" to signify a risk-on environment when S is positive. Second, we calculate direction, defined as the weekly change in the BRS multi-asset score. This represents investors' desire to take on additional risk. Change is designated by "C," and we use the notation "$C > 0$" to signify a strategy that allocates to risk when change is positive. Third, we combine both the sign and direction, requiring that both are positive, for example. This is signified by "S and $C > 0$." To some extent, this combined requirement captures the confidence investors have in building risk positions. That is, when investors are already exhibiting risk-seeking behavior, are they willing to take on more risk?

To measure the performance of these BRS multi-asset, score-driven forecasts of asset allocation, we need a benchmark. If we use these BRS-driven measures for dynamic asset allocation, it makes sense to specify a passive allocation that reflects a static level of sentiment, beyond which the active allocation should outperform. In this case, our benchmark is the performance of a strategy weighted 50% in cash and 50% in an equally weighted index across four risky assets: the MSCI AC

Exhibit 5

Multi-Asset and Asset-level Score, Average Correlations with Asset Class



Source: State Street Associates, Thomson Datastream.

Exhibit 6

Three Signals

–**Sign**: the sign of the score—the sign of aggregate sentiment captures the environment or attitude towards risk.

–**Direction**: change (C) = level (t) – level (t – 1)—if overall sentiment is improving, a desire to take on additional risk is indicated.

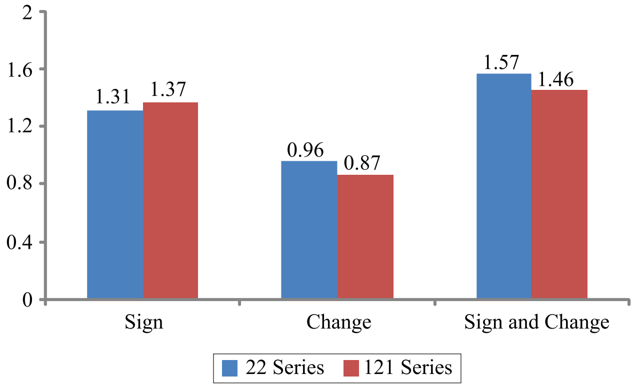
–**Momentum**: Sign and Direction—if investors are risk seeking and willing to take on more risk, the confidence to increase exposure is highlighted.

Source: State Street Associates.

World equity total return index, the Barclays U.S. Corporate High Yield bond total return index, the JPM ELMI+ composite currency total return index, and the S&P GSCI total return index. We examine the performance of a positive sign (S > 0), a positive change in sentiment (C > 0), and the combined sign and change (both S > 0 and C > 0), where we allocate to the risky assets when S > 0, or C > 0, or S and C > 0. When these conditions are not met, we invest in the Barclays U.S. Treasury Bellwethers 3M total return index. Trading models generated from the scorecard signal incorporate a three-day flow lag and are rebalanced weekly. Performance is evaluated from July 2002 to March 2013.

We find that the 22-element BRS multi-asset score performs in a consistent manner with the broader 121-measure in timing asset allocation (Exhibit 7). On aggregate, the sign of sentiment helps the timing decision, outperforming the 50/50 cash/risky-asset benchmark. However, combining the sign and change (S and C) results in an even more powerful signal in terms of risk-adjusted measures (Exhibit 8). A striking result is

Exhibit 7
Multi-Asset Score, Reward-to-Risk Ratios



Source: State Street Associates, Thomson Datastream.

that, when we use the combination of sign and change, risk-adjusted performance measures increase dramatically. Indeed, this confidence indicator (S and C > 0) reveals periods of time when risk-seeking investors are willing to take on more risk, and the confidence to increase exposure is on the rise.

Timing Asset Classes

Given its construction as an aggregation of flow signals across asset classes, the BRS multi-asset score may be valuable not only in timing the cash/risky asset decision, but also in timing asset-specific risk. To find out, we test how the BRS multi-asset score performs in allocating actively across the same four risky asset classes (MSCI AC World equity total return index, the Barclays U.S. Corporate High Yield bond total return index, the JPM ELMI+ composite currency total return index, and the S&P GSCI total return index), allocating again toward more risky assets alternately when the score's sign is positive, S > 0, the BRS score's change is positive, C > 0, and both the sign and change are positive, S and C> 0. In each case, we invest in cash when the relevant ">" condition is not met. Using the BRS multi-asset score, we find that each of the three timing strategies—S, C, and S and C—generally beats the benchmark in terms of reward-to-risk ratios (Exhibit 9). In general, S and C is relatively more informative in timing the risky asset decision.

Timing Asset Classes using Asset-Level Scores

Finally, we test how well the individual asset-level scores (as opposed to the BRS multi-asset score) can allocate to asset-specific risk. Although it is intuitive to apply the aggregate asset-level scores to separate returns in their respective asset classes, our expectation is that the BRS multi-asset score can better predict broader market moves. Certainly, aggregated gauges of investor sentiment have become increasingly important, given the high levels of global financial market integration and similar developed-market central bank policies that have driven cross-asset return correlations higher.

Using individual asset-level scores for the 22 series, we time the asset-class indices. In this iteration, sign clearly does best. Using similar logic, and applying scores to the MSCI AC World equity total return index, the Barclays U.S. Corporate High Yield bond total return index, the JPM ELMI+ composite currency total return index, and the S&P GSCI total return index, we find that S > 0 outperforms the S and C > 0 signal consistently (Exhibit 10). Change seems to have a negative effect on performance. This could be the result of the higher proportion of zero changes, given the fewer elements in asset-level scores for the 22 series.

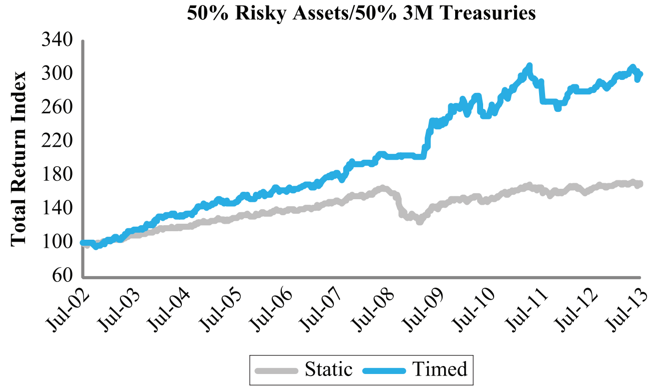
Although there is informative content in asset-level scores, the BRS multi-asset score performs better in timing risky assets. Indeed, there is only one instance in which the asset-level score outperforms our BRS multi-asset score in timing individual asset-class returns on a risk-adjusted basis: the sign for the commodity score. Our BRS multi-asset score performs better in timing equity, high-yield fixed income, and emerging-market currency returns, indicating the power of combining sentiment across asset classes.

Jensen's Alpha

In addition, we calculated Jensen's alpha across four asset classes separately (Exhibits 9 and 10). We regress weekly timed returns in excess of a weekly Treasury rate on the excess market return for each asset class from July 2002 to July 2013. Using the sign of the BRS multi-asset score, we find that all asset-class alphas are statistically significant at the 10% level (with fixed income and FX significant at the 5% level), and greater than 3% in magnitude on an annualized basis. Combining the sign

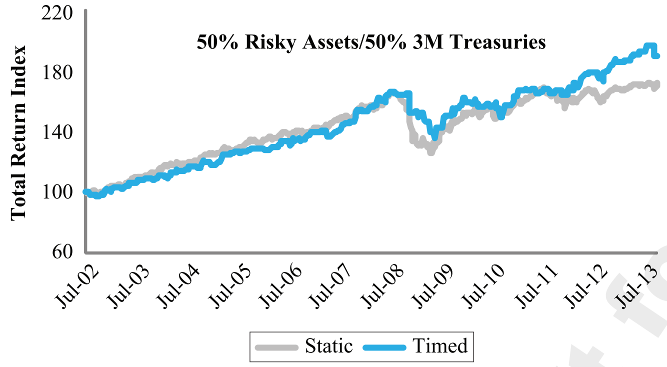
EXHIBIT 8
Multi-Asset Score, 22 Element Results

Sign



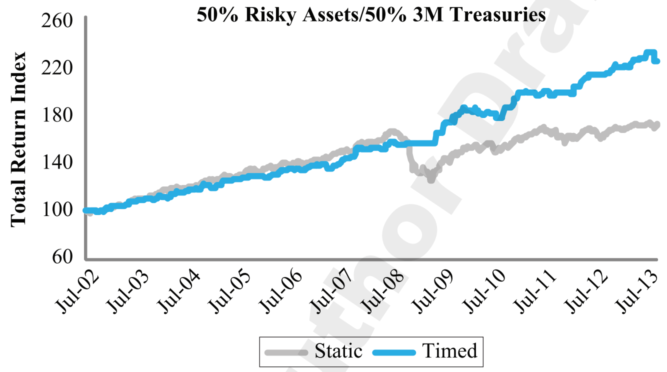
	Benchmark	Timed	Active
Annualized Return	5.0%	10.5%	5.2%
Annualized Volatility	5.9%	8.0%	5.9%
Reward-to-Risk Ratio	0.86	1.31	0.90
Maximum Drawdown	–24.4%	–16.9%	

Change



	Benchmark	Timed	Active
Annualized Return	5.0%	6.0%	5.2%
Annualized Volatility	5.9%	6.2%	5.9%
Reward-to-Risk Ratio	0.86	0.96	0.16
Maximum Drawdown	–24.4%	–18.8%	

Sign & Change



	Benchmark	Timed	Active
Annualized Return	5.0%	7.5%	2.3%
Annualized Volatility	5.9%	4.8%	5.9%
Reward-to-Risk Ratio	0.86	1.57	0.39
Maximum Drawdown	–24.4%	–5.1%	

Source: State Street Associates, Thomson Datastream.

with change also generates significant alphas for equities, fixed income, and currencies. When we use individual asset-level scores to time the risky benchmark indices, $S > 0$ again outperforms S and $C > 0$ in terms of annualized alpha, similar to the results we see in the asset-class backtests using asset-level scores.

CONCLUSION

Higher levels of global financial market development and integration, as well as increased central bank policy initiatives by major developed-market policymakers (asset purchase programs/financial repression/

EXHIBIT 9

Multi-Asset Score—Timing Asset Classes (Reward-to-Risk Ratios and Jensen's Alpha)

		MSCI AC	Barclays U.S. High Yield	JPM ELMI+	S&P GSCI
Reward-to-risk	**Index**	0.38	1.25	0.97	0.16
	S	0.75	2.08	1.47	0.54
	C	0.62	1.37	0.79	0.15
	S and C	1.04	1.78	1.27	0.51
Annualized Alpha	**S**	5.73%**	5.21%*	3.23%*	6.74%**
	C	3.42%	1.9%**	0.00%	–0.36%
	S and C	6.34%*	2.45%*	1.58%**	3.34%
Beta	**S**	0.443*	0.37*	0.511*	0.589*
	C	0.292*	0.274*	0.347*	0.305*
	S and C	0.189*	0.123*	0.204*	0.197*

Source: State Street Associates, Thomson Datastream.

EXHIBIT 10

Asset-level Scores—Timing Asset Classes (Reward-to-Risk Ratios and Jensen's Alpha)

		MSCI AC	Barclays U.S. High Yield	JPM ELMI+	S&P GSCI
Reward-to-risk	**Index**	0.38	1.25	0.97	0.16
	S	0.69	1.63	1.17	0.56
	C	–0.11	0.90	0.51	0.01
	S and C	–0.07	0.75	0.52	0.15
Annualized Alpha	**S**	4.35%	5.61%*	0.26%	4.99%
	C	–3.92%	–0.76%	–2.29%*	0.09%
	S and C	–2.60%	–0.97%	–1.240%**	1.39%
Beta	**S**	0.331*	0.518*	0.367*	0.327*
	C	0.231*	0.202*	0.229*	0.221*
	S and C	0.104*	0.188*	0.111*	0.0963*

Source: State Street Associates, Thomson Datastream.

quantitative easing), have led to an increase in cross-asset return correlations, highlighting the need for broader measures of market sentiment. Using an extensive array of behavioral indicators that reach across asset classes and various dimensions of investor behavior, we find that similarities between the behavior of the portfolios that comprise our flow indicators, and differences between our portfolios' behavior and the behavior of the rest of the market, make aggregate measures of investor behavior informative.

We compute a summary BRS multi-asset score to aggregate what we think of as the risk on or risk off flows across assets. Because the behavioral measures generally—and flow measures in particular—display properties that are reasonably consistent across asset classes, we expect that aggregates that sum across these flows display these properties more strongly. Thus, if flows are persistent and positively correlated with asset returns, we should find aggregations to be even more strongly persistent and positively correlated with aggregate asset returns.

We demonstrate that:

- The compact 22-element behavioral risk scorecard is a valuable gauge of aggregate sentiment and informatively summarizes the broader set of flows.
- Knowing the sign as well as the direction and momentum of the BRS multi-asset score can improve the timing of asset class specific risk as well as assist in making informed tactical asset allocation decisions.
- In aggregate, multi-asset flows enhance risk-adjusted performance and risk timing over individual asset-level scores alone.

This is our first look at aggregating risk from a multi-asset class perspective across our suite of behavioral indicators and capturing trading sentiment more comprehensively. In the future, overlaying trading sentiment with positioning risk, as measured by holdings, and investor consensus, as measured by agreement, will add further dimensions to our insights into behavioral risk.

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ENDNOTE

[1]A conditional percentile ensures that inflows receive a percentile ranking above the 50th percentile, while outflows receive a ranking below the 50th percentile. Please note that the sector equity flow indicator (cyclical minus defensive sectors) and equity borrowing indicator (EBI) (defensive minus cyclical sectors) percentiles are unconditional, as we're taking the aggregate differences across sectors and, in this case, relative momentum can gauge sentiment. The look back period for percentile rankings for the EBI and the corporate bond flow indicator (CBFI) high yield-investment grade flow is two years, given the later starting dates.

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