INSTITUTIONAL ADVISORY & SOLUTIONS

WHAT'S IN YOUR REAL ASSET PORTFOLIO?

Introducing RASA™

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In prior research we highlighted the diversity of real assets in terms of their sensitivities to the equity and bond markets and to macroeconomic factors such as growth and inflation. We now extend our analysis to real asset portfolios. Do portfolios exhibit similar characteristics and performance? Or, like the real assets themselves, do real asset portfolios display heterogeneity, with a given portfolio serving a particular investment goal and purpose? We use our Real Asset Sensitivity Analysis (RASA™) framework to help CIOs estimate the macroeconomic and market sensitivities of a real asset portfolio.

Institutional investors have increased their allocations to real assets, either assembling the real asset portfolio themselves from the ground up; investing in a third-party real asset fund; or some combination of the two. To illustrate the diversity of real asset portfolios, we examine third-party public, liquid, real asset funds. RASA sensitivities differ considerably across funds and can differ even when funds have similar broad asset allocations. Institutional investors can use RASA to gauge whether a real asset fund, or custom portfolio, aligns with their investment objectives.

Using RASA, we identify fund groups that are likely suited for distinct economic environments. An investor can use this information to select funds that may achieve a targeted investment objective-oriented strategy such as Inflation Protection, Growth, or Growth Protection.

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Figure 1: Fund Attributes

Real Asset Funds	Investment Approach	Investment Focus	Vehicle Type	Return Method
#1	Active	TAA	SA	Gross
#2	Active	TAA	SA	Gross
#3	Passive	SAA	CF	Gross
#4	Active	TAA	SA	Gross
#5	Active	TAA	PF	Net
#6	Active	TAA	SA	Gross
#7	Active	SAA	SA	Gross
#8	Active	TAA	SA	Gross
#9	Active	TAA	SA	Gross
#10	Active	TAA	SA	Gross
#11	Active	TAA	PF	Net
#12	Active	TAA	SA	Gross
#13	Active	TAA	CF	Net
#14	Active	SAA	PF	Net
#15	Active	TAA	PF	Gross
#16	Active	TAA	SA	Gross
#17	Passive	SAA	SA	Gross
#18	Active	TAA	SA	Gross
#19	Active	TAA	SA	Gross
#20	Active	SAA	SA	Gross

Note: SA – Separate Account, CF – Commingled Fund, and PF – Pooled Fund. Reported performance of funds may either be gross of fees or net of fees. 4 of the 20 funds reported net of fees performance.

Source: eVestment and PGIM IAS.

In prior research we highlighted the diversity of individual real assets in terms of their sensitivities to the equity and bond markets and to macroeconomic factors such as growth and inflation.[1] We now extend our analysis to real asset *portfolios*. In the past decade institutions have increased their portfolio allocations to real assets, either assembling the real asset portfolio themselves from the ground up; investing in a third-party real asset fund; or some combination of the two.[2] Since real assets are a heterogeneous asset class, do real asset portfolios also display such heterogeneity? Or, do real asset portfolios exhibit similar characteristics and performance?

To analyze this issue, we examine the diversity across third-party public, liquid, real asset *funds*. There has been rapid growth in these fund offerings. In fact, while only five funds existed prior to the financial crisis, by December 2019 there were over two dozen. Despite sharing the term “real assets” in their name, we show that these funds differ considerably in terms of their market and macroeconomic factor sensitivities. With such disparity across several important investment dimensions, how can a CIO best identify the true underlying investment objective of any real asset fund, or of their own portfolio?

We examine real asset investment fund data available in the eVestment database (self-reported), selecting funds with “real asset,” “real return,” or “inflation” in their names and only include multi-asset funds (*i.e.,* we exclude TIPS-only funds).[3] We identify 20 currently active real asset funds (anonymously identified) with at least 7y of performance history (Figure 1). These funds, with a total AUM of about $25b, are liquid and are available *via* several vehicles: separate accounts, mutual funds, commingled funds and

1 See H. Parikh, and W. Zhang, “The Diversity of Real Assets: Portfolio Construction for Institutional Investors,” PGIM IAS, June 2019.

2 We examine the real asset portfolios of public pension plans over the past decade in “Institutional Real Asset Investing: Peer Group Comparison Across Public Plans,” H. Parikh and J. Marcial, PGIM IAS, forthcoming.

3 Most of the 20 funds are found in eVestment’s liquid “real assets” universe but some reside in other universes (*e.g.,* “global balanced” or “tactical asset allocation”). For this study, due to portfolio data limitations, we focus on liquid real asset funds that invest only in public assets. Very few funds invest in private real assets with enough transparency to be offered as open-end funds. Funds that invest in private assets are offered as either open-end interval funds or as closed-end funds.

ETFs. One-third of these assets are in institutional defined contribution (DC) plans, one-third in institutional corporate, public and E&F plans and the remainder in sub-advised, retail and other categories. DC plan sponsors need the daily liquidity offered by these funds. Institutional investors allocate to these funds to manage cash inflows and outflows, and to increase the capacity of their overall real asset allocations.

We first survey the funds' characteristics: investment objectives, benchmarks and investment styles. Then, we analyze their asset allocations (as of June 2019) and historical performance. We then examine their sensitivities to various macroeconomic and financial market variables, at both short and long horizons, using our **R**eal **A**sset **S**ensitivity **A**nalysis (RASA™) framework.[4] Our analysis can be extended to an institutional portfolio containing a mix of both public and private real assets and funds. Finally, using each fund's estimated recent RASA sensitivities, we cluster these funds and identify the economic environment likely best suited for each fund cluster.

Fund Characteristics

There is a remarkable variety of *stated* investment objectives across our sample of real asset funds: "Seek total returns greater than inflation;" "Provide diversification from stocks and bonds;" and "Outperform but match the total return volatility of TIPS;" to name a few. Along with these diverse investment objectives, the benchmark choice is equally varied. Some funds use the Consumer Price Index (CPI) + x% as their benchmark, while others use TIPS or a natural resource equity index. Many funds also use a blended benchmark, a weighted average of various (real) asset class level indexes (*e.g.,* 33% S&P Global Natural Resources, 33% FTSE EPRA NAREIT Developed and 34% Bloomberg Commodity Index).[5]

To achieve their objectives, funds adopt different investment approaches such as being active or passive (Figure 1). The asset allocation style (*i.e.,* investment focus) can be either static or dynamic/tactical. Funds also employ different weighting schemes such as risk parity.

Real Asset Fund Asset Allocations

Asset-Class Cluster Analysis

Over their investment history the funds in our sample have invested in 21 different asset categories.[6] To summarize asset class exposures, we use "cluster analysis" to group together similar asset classes. Cluster analysis is a statistical tool that groups assets based on the similarity of their historical returns (see Appendix). We cluster the 21 different asset categories into seven distinct groups (Figure 2).

The largest cluster by number of assets includes fixed income, TIPS, cash and currency assets. We label this cluster "FICC." The second largest cluster is "Other Equities," infrastructure equities, REITs, global equities and US equities. Natural Resource Equities, EM Equities, MLPs, Commodities and Gold each form their own cluster.

Average Allocation Weights Across Funds – Last 7y

Having grouped the asset classes into seven clusters, we estimate each fund's average historical cluster allocation weights. A fund's average weights across clusters help identify the systematic drivers of the fund's returns over the past 7y. To estimate these weights, we use style analysis (*i.e.,* multivariable regression) to examine the sensitivity of each fund's historical returns to each cluster's returns (Figure 3).[7]

We find that funds share a large average allocation to the FICC, Other Equities, and Commodities clusters, with a median weight greater than 10% to each. However, there are large differences in weights across funds. For example, average allocations to the Natural Resource Equities cluster ranged from 0% to 56% across funds; allocations to the Commodities cluster ranged from 0% to 32%; and allocations to Other Equities ranged from 0% to 62%. Similarly, allocations to the FICC cluster ranged from 5% to 97% across funds.

Funds tend to have cluster concentrations. At the cluster level, the Herfindahl-Hirschman Index (HHI) ranges from 21% to 94% across funds, with an average of 40%, signifying that funds concentrate in certain clusters.[8]

4 See H. Parikh, "Institutional Gold!" PGIM IAS, November 2019, which details the methodology underlying RASA™.

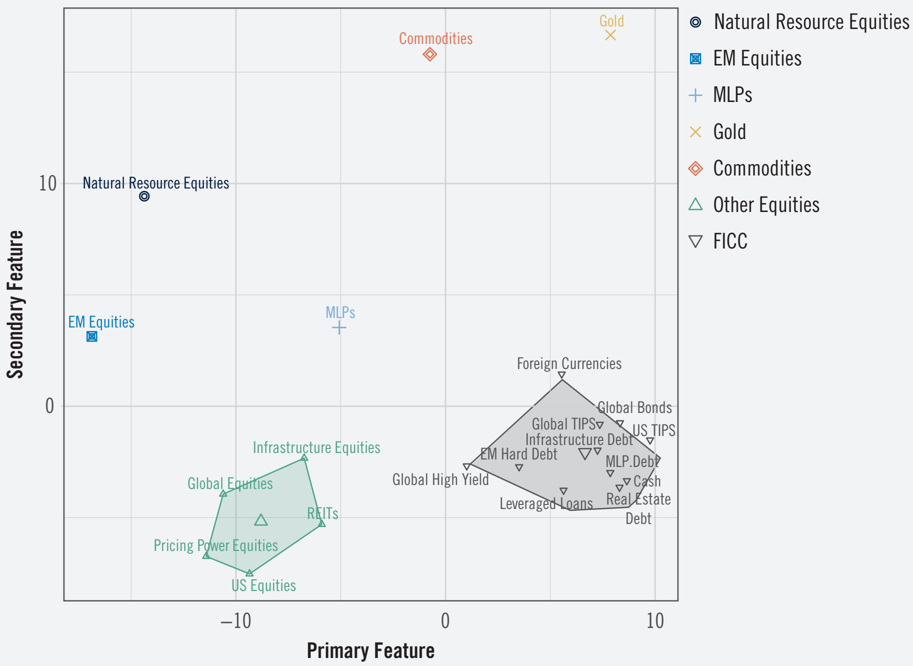
5 EPRA – European Public Real Estate Association; NAREIT – National Association of Real Estate Investment Trusts.

6 For example, funds allocate to real assets like MLPs, gold, real estate debt; traditional fixed income assets like high yield debt, EM (hard currency) debt and floating rate leveraged loans; and traditional equities like S&P 500, stocks with pricing power, etc.

7 Cluster returns are equally-weighted returns of each of the asset classes within the cluster. The median style analysis R^2 was 0.86. One fund had an outlier R^2 of 0.23.

8 A fund equally weighted across the seven clusters would have an HHI of 14.3% while a fund with a single cluster would have an HHI of 100%.

Figure 2: Asset-Level Clusters – Similarity of Returns



Note: This figure shows how close the 21 different assets are to each other in terms of their historical total returns from January 1999 to August 2019. The Primary Feature axis is the first principal component value and the Secondary Feature axis is the second principal component value of these 21 assets returns. See appendix for benchmark descriptions. For illustrative purposes only.

Source: Datastream, S&P Capital IQ, and PGIM IAS.

Figure 3: Asset Cluster Weights, Across Funds; Cluster Concentrations, by Fund

Figure 3a
7y Average Weights, by Cluster, across Funds

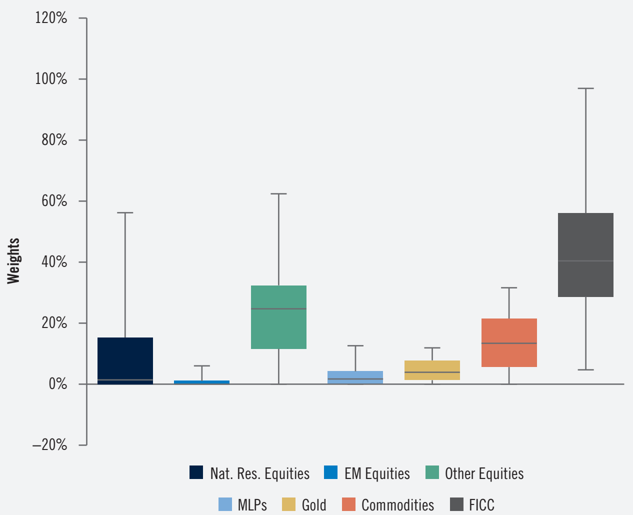
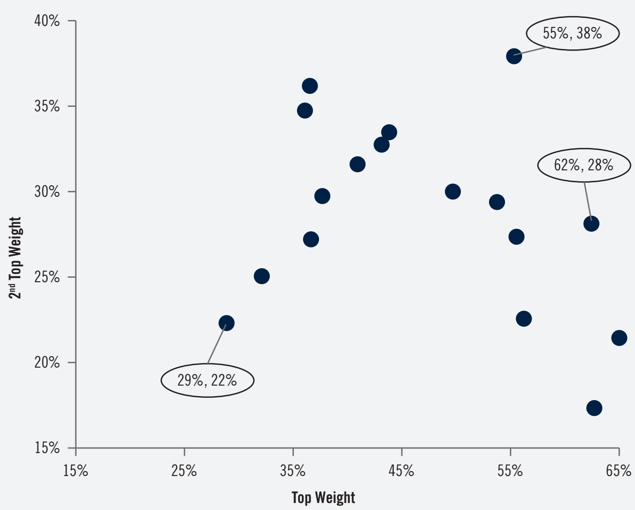


Figure 3b
Top Two Cluster Weights, by Fund



Note: To estimate 7y average asset class weights we conduct return-based style analysis using data for the period from July 2012 to June 2019. Figure 3a shows range of weights across funds in each of the seven asset-level clusters. Figure 3b shows weights in top two asset-level clusters for each of the funds. For illustrative purposes only. Model weights may differ from actual fund weights.

Source: eVestment, Datastream, S&P Capital IQ, and PGIM IAS.

Figure 4: Recent Weights (%), by Cluster, 20 Funds, June 2019

Real Asset Fund	Natural Resource Equities	EM Equities	Infrastructure, REITs and Other Equities	MLPs	Commodities	Gold	FICC	HHI (Concentration)
#1	19.4%	0.0%	48.9%	0.0%	34.2%	0.0%	–2.4%	39.4%
#2	7.0%	0.0%	48.9%	1.7%	2.0%	0.0%	40.4%	40.8%
#3	0.0%	0.0%	36.6%	0.0%	22.2%	0.0%	41.3%	35.3%
#4	19.0%	0.0%	38.0%	0.0%	25.0%	3.0%	15.0%	26.6%
#5	0.0%	0.0%	9.4%	0.0%	25.3%	0.0%	65.3%	49.9%
#8	0.0%	5.0%	22.5%	12.5%	7.5%	0.0%	52.5%	35.0%
#10	0.0%	0.0%	62.7%	0.0%	0.0%	0.0%	37.4%	53.2%
#11	5.2%	0.0%	36.6%	5.7%	14.7%	5.1%	32.7%	27.1%
#12	0.0%	0.0%	9.6%	0.0%	19.7%	9.0%	61.7%	43.7%
#13	0.0%	0.0%	34.8%	0.0%	25.1%	0.0%	40.1%	34.5%
#14	22.0%	0.0%	28.0%	6.0%	11.0%	0.0%	33.0%	25.1%
#16	0.0%	0.0%	70.6%	14.3%	0.0%	0.0%	15.1%	54.2%
#17	25.0%	0.0%	25.0%	0.0%	25.0%	0.0%	25.0%	25.0%
#18	41.0%	0.0%	0.0%	0.0%	13.0%	0.0%	46.0%	39.7%
#19	63.4%	0.0%	0.0%	0.0%	18.8%	0.0%	17.8%	46.9%
#20	45.0%	0.0%	10.0%	0.0%	25.0%	0.0%	20.0%	31.5%
#21	10.0%	0.0%	63.0%	0.0%	12.0%	0.0%	15.0%	44.4%
#22	0.0%	0.0%	76.4%	5.0%	0.0%	0.0%	18.6%	62.1%
#23	31.3%	0.0%	27.5%	0.0%	20.3%	0.0%	21.0%	25.8%
#24	59.7%	0.0%	5.0%	0.0%	8.2%	0.0%	27.1%	43.9%

Note: For illustrative purposes only.
Source: PGIM IAS.

Recent Weights (June 2019)

Figure 4 shows asset allocations (as of June 2019), by cluster, for the 20 funds.[9] Some funds have allocations as high as 65% to the FICC cluster while others have allocations as high as 63% to the Other Equities cluster.

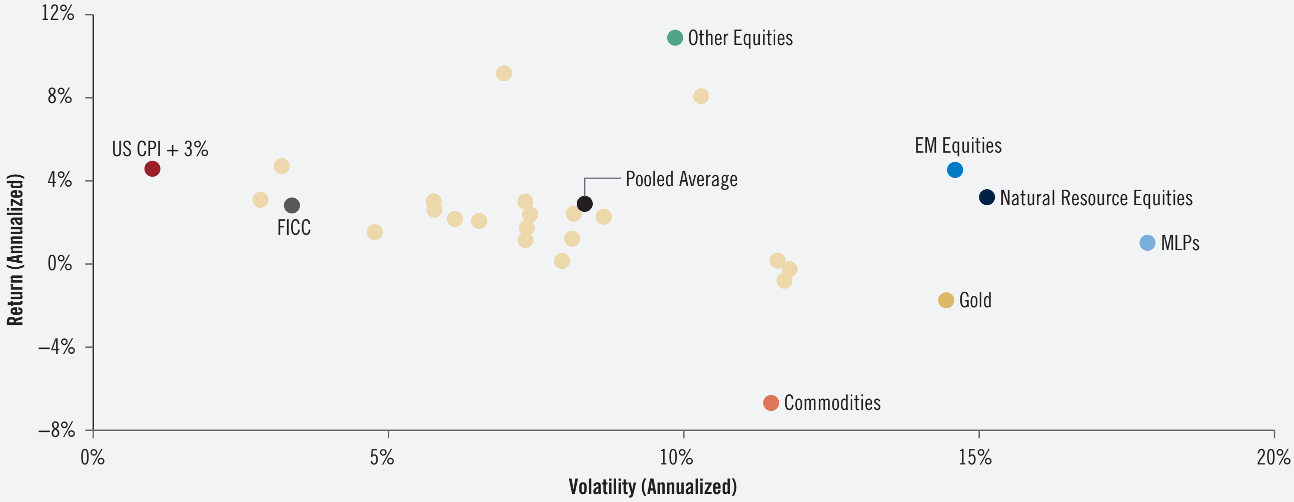
Historical Performance of Real Asset Funds

On average, funds exhibited moderate annual total return volatility (8.3%/y). However, as shown in Figure 5, some funds had equity-like volatility (~11%/y) while others had bond-like volatility (~4%/y). During our 7y period, a low-inflation period, the average annual fund return was 2.9%/y, lower than the common CPI + 3%/y (4.6%/y) target, but about the same as the FICC cluster (2.8%/y) (Figure 5). Two real assets clusters (Natural Resource Equities and Commodities) had lower returns and higher annual volatility than the Other Equities cluster. Over the data period, the funds in our sample did not generally achieve their stated investment objectives.

However, there were some standout funds with higher returns and lower annual volatility than FICC, or with returns and annual volatility closer to Other Equities.

9 We collected recent asset allocations from fund factsheets as they were not available from eVestment. We use these asset class weights later to conduct RASA analysis. Recent asset allocations for four funds with more than 7y performance history were not available. So, for our subsequent analysis we included four other funds with performance history of less than 7y.

Figure 5: 7y Performance Record
(USD returns; July 2012 – June 2019)



Note: For illustrative purposes only. Past performance is not a guarantee or reliable indicator of future results. Four of 20 funds reported net of fees performance and the rest reported gross of fees performance (Figure 1).

Source: eVestment, Datastream, S&P Capital IQ, and PGIM IAS.

Fund Sensitivities to Market and Macroeconomic Factors – RASA™ Analysis

Using the RASA™ framework we report average financial market and macroeconomic sensitivities at both a short horizon (3m – matching performance reporting frequency) and at a longer horizon (24m – which may match a CIO's investment horizon). These fund-level sensitivities can help a CIO gauge if a real asset fund matches their investment objectives.

RASA Sensitivities Using Recent Weights (June 2019)

While funds dynamically change their asset allocation weights, we use their *recent* allocations to estimate their current sensitivity to actual inflation[10] and growth.[11] Figure 6 shows a wide range of inflation and growth sensitivities across funds.[12] CPI betas, at a 3m horizon, range from 1.4 to 5.0, and CFNAI (Chicago Fed National Activity Index) betas range from 0.005 to 0.027.

RASA also generates confidence intervals for the true beta.[13] Figure 6 presents 90% confidence interval bands for CPI and CFNAI betas. Five out of our 20 funds may have a true CPI beta close to or lower than zero! Similarly, even high average CFNAI beta funds like #20 and #21 may have a true beta close to zero.

Using recent weights, we find that fund macroeconomic sensitivities increase in magnitude with the investment horizon (Figure 7). Although not shown, funds generally have the same relative ranking in terms of sensitivities regardless of the horizon. But this is not always the case for asset classes. Comparing the CPI 3m vs. CPI 24m betas for S&P 500 and Treasury 10y, even the signs of the betas flip. So, real asset funds have provided stable inflation sensitivity compared to stocks or bonds. In addition, they provide growth sensitivity somewhere between that of stocks and bonds.[14]

10 We chose actual inflation in our analysis as these data are available at higher frequency (*i.e.*, monthly). The correlation between actual inflation and expected inflation (from Survey of Professional Forecasters), available quarterly, is high (0.85) as is the correlation between quarter-over-quarter changes (0.74). Similarly, the correlation of actual inflation to inflation surprises (actual inflation in excess of expected inflation) is high (0.74). In "Diversity of Real Assets" we assess real asset sensitivities to both inflation and inflation surprises. Generally, the ranking of the 13 real assets based on their sensitivities to either were similar (rank correlation of 0.96).

11 Alternatively, we could use a benchmark's asset weights. However, not all funds had benchmark weights for asset classes in their portfolios.

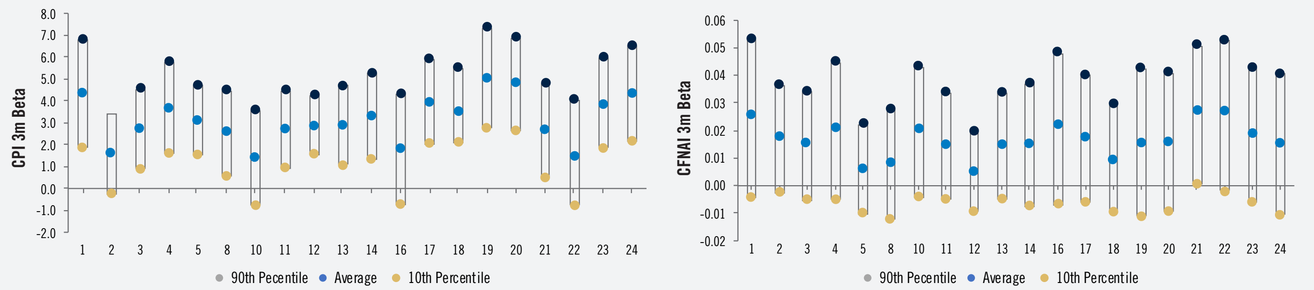
12 The Appendix contains robustness checks. The ranking of funds based on their performance in inflation/growth scenarios matches the ranking of the funds based on inflation/growth betas. This confirms the robustness of the estimated fund sensitivities.

13 Parikh (2019) shows how such uncertainty (*i.e.,* estimation error) can be incorporated into portfolio construction. Confidence intervals vary with return horizon and data period. We do not make any distributional assumptions for the estimator, unlike mathematically calculated confidence intervals, and for the underlying return process we only assume that horizon returns are independent and identically distributed.

14 While not reported here, the average R^2 regression statistics of fund returns on CPI and CFNAI at 3m horizons are generally lower than the R^2 at 24m horizons, suggesting that macroeconomic variables better explain fund performance at longer horizons.

Figure 6: Fund Sensitivities to CPI & CFNAI

Betas, Confidence Intervals (Recent Weights)

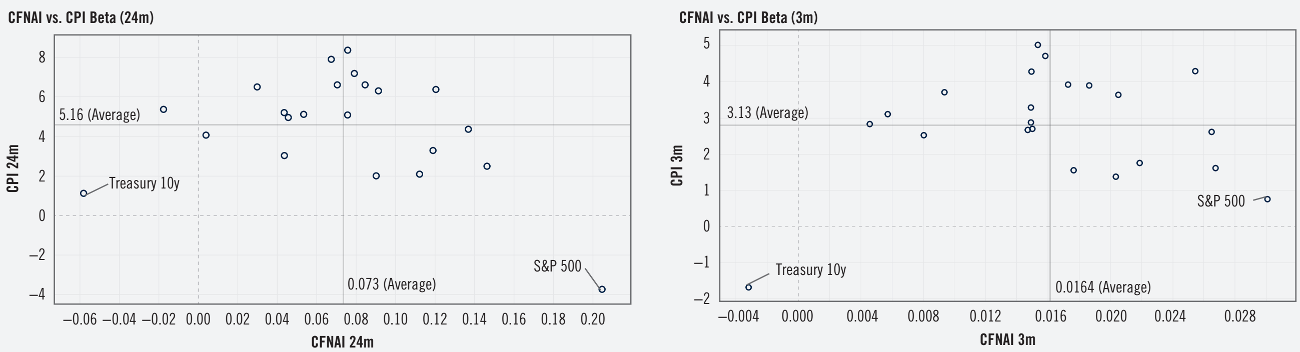


Note: Fund sensitivities are estimated using data for the period from January 1999 – August 2019. Recent weights are as of 6/30/2019. For illustrative purposes only.

Source: eVestment, Datastream, S&P Capital IQ, Federal Reserve Bank of Chicago, and PGIM IAS.

Figure 7: Fund Sensitivities to CPI and CFNAI; 3m vs. 24m Horizons

20 Real Asset Funds; 10y Treasury & S&P500 (Recent Weights)



Note: Recent weights are as of 6/30/2019. For illustrative purposes only.

Source: eVestment, Datastream, S&P Capital IQ, Federal Reserve Bank of Chicago, and PGIM IAS.

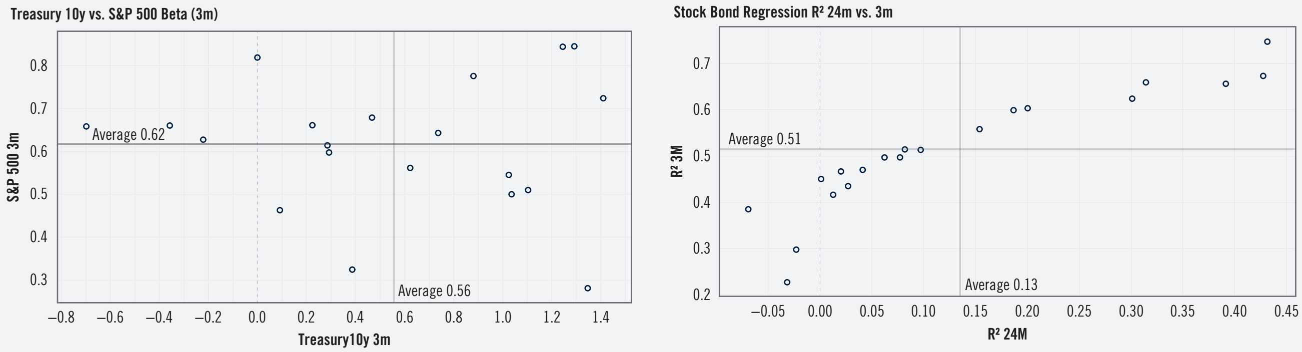
A similar picture emerges when we compare funds' sensitivities – using recent (June 2019) weights – to stocks and bonds (*i.e.*, the diversification potential of including real assets in institutional portfolios). Some funds have very high equity betas while others have high bond betas (Figure 8). Since the R^2s at the long horizon are lower than at the short horizon, we infer that these funds collectively offer different sources of returns at longer horizons.

RASA analysis highlights that the sensitivity of two funds (say, to the CPI) can be very different despite having similar asset allocations. For example, funds #10 and #19 (see Figure 4) have similar allocations to equities, but one has a CPI beta of 2.1 while the other has a beta of 8.4. Why the large difference? Fund #19 invests in the Natural Resource Equities cluster while #10 invests in Other Equities. Similarly, funds #17 and #8 have very similar allocation to equities but their CPI betas are again very different (6.6 vs. 3.0, respectively) because #8 invests in the MLP and EM Equities clusters while #17 invests in the Natural Resource Equities cluster.

However, cluster weights do not tell the full story which is why CIOs could benefit from RASA. While funds with greater FICC cluster allocations tend to have lower CFNAI betas, funds achieved this sensitivity differently. For example, funds #12 and #5 have similar allocations to the FICC cluster, but #12 holds only inflation linkers whereas #5 allocates between leveraged loans and linkers. These differences in allocations produce differences in CPI betas (5.4 for #12 and 4.1 for #5).

These results suggest that in addition to funds' asset cluster weights, CIOs may want to evaluate funds based on their RASA characteristics.

Figure 8: S&P 500 and Treasury 10y Sensitivity Comparison
20 Real Asset Funds (Recent Weights)



Note: Recent weights are as of 6/30/2019. For illustrative purposes only.

Source: eVestment, Datastream, S&P Capital IQ, Federal Reserve Bank of Chicago, and PGIM IAS.

RASA Sensitivities Using Average Historical Weights (July 2012 – June 2019)

Instead of recent asset allocations we now use average *historical* weights from our earlier style analysis to simulate fund returns and estimate RASA sensitivities. How do the sensitivities compare? The correlation between simulated fund returns using either average weights or recent weights (rebalanced monthly) is high, ranging from 0.91 – 0.99 (averaging 0.96).[15]

Generally, we find that the RASA sensitivities, both CPI and CFNAI, estimated using recent allocations are higher than those estimated with historical weights. This is the case at both 3m and 24m horizons for about two-thirds of the funds.[16] The median fund's 3m and 24m CPI betas using recent weights (3.0 and 5.2) are higher than those using historical weights (2.7 and 3.8). Similarly, the median fund's 3m and 24m CFNAI betas using recent weights (0.015 and 0.069) are higher than those using historical weights (0.012 and 0.058). Perhaps fund managers have improved their growth and inflation outlooks?

While the magnitudes of sensitivities are currently higher (versus historical), we find that the relative rankings across funds are similar. In other words, a fund's beta to CPI or CFNAI tends to be high (or, low), relative to other funds, irrespective of which asset class cluster weights are used (average historical or recent). Figure 9 compares the CPI and CFNAI 3m betas estimated using fund recent weights and average weights.

We also compare funds' stock-bond regression R^2s. The median 3m and 24m R^2s are lower with recent weights compared to those based on average historical weights (0.48 vs. 0.57 for 3m; 0.06 vs. 0.20 for 24m). So, these funds are more diversifying recently than historically.

Overall, comparing recent weights with historical average weights provide a better perspective for how funds are poised for certain economic environments, which we explore below.

Fund-Level Cluster Analysis

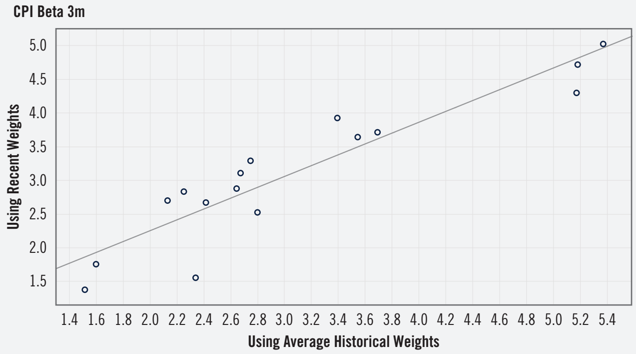
With so much disparity in funds across dimensions like asset cluster weights and RASA sensitivities, CIOs might wonder how best to identify those real asset funds that align with their investment objectives. CIOs may want to invest in funds that are either similar, or different, in order to diversify within or across such dimensions.

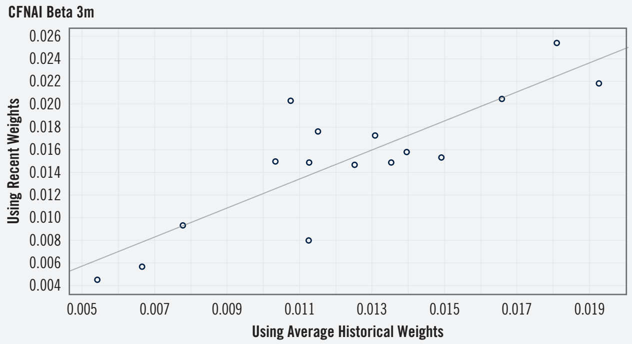
Using each fund's estimated recent RASA sensitivities, we cluster the 20 funds (as we did for asset classes earlier). To form fund clusters, we use six fund characteristics – 3m and 24m CPI & CFNAI betas and stock-bond regression R^2s. In addition to the funds, we also include real asset strategy portfolios constructed to meet specific investment objectives – **inflation protection,**

15 The average tracking error volatility (implied by the difference between recent and average allocations) ranged from 2% – 8.2% (averaging 4.4%), suggesting that some funds are more active than others.

16 16 of the 20 funds with 7y history have reported recent weights. Therefore, we make comparisons for 16 funds. Fund sensitivities are estimated using simulated fund returns for the period from January 1999 to August 2019.

Figure 9: RASA Sensitivity Comparison
Using Average Historical vs. Recent Weights





Note: Recent weights are as of 6/30/2019. For illustrative purposes only.

Source: eVestment, Datastream, S&P Capital IQ, Federal Reserve Bank of Chicago, and PGIM IAS.

diversification, and **stagnation protection**.[17] Adding these strategy portfolios to the cluster analysis helps identify the investment objective of a fund cluster.[18]

Notably, none of the fund clusters include any of the three real asset strategy portfolios (Figure 10), highlighting the advantage of the strategy portfolios for CIOs with clearly defined objectives for their real asset allocations.

Based on the funds' RASA sensitivities in each of the four clusters, we can identify the economic environment best suited for each fund cluster. Each cluster is focused on a distinct economic environment – **overheating** (high-inflation/high-growth), **ideal** (low-inflation/high-growth), **muddled** (mid-inflation/mid-growth) and **stagflation** (high-inflation/low-growth) (Figure 11). No cluster is focused on stagnation (low-inflation/low-growth).[19] These results can help a CIO construct their own strategy portfolio using one or more funds.

For example, an **Inflation Protection** objective strategy is expected to outperform in both overheating and stagflation environments. So, a CIO may want to include funds from both overheating and stagflation-focused fund clusters. Alternatively, a CIO seeking a **Growth** strategy may want to allocate to funds from the overheating and ideal-focused clusters. A CIO seeking a **Growth Protection** strategy may wish to allocate to funds from the stagflation-focused cluster and construct a bespoke **Stagnation Protection** strategy. Finally, a CIO seeking returns that differ from stocks and bonds may construct a bespoke **Diversification** strategy.

Real Asset Investing in Institutional Defined Contribution

The real asset funds we analyze are liquid (generally, daily liquidity) and are used by institutional DC plans. A real asset fund may be part of a plan's menu or as a component of a target date fund. In either case, DC plan sponsors need to know if a fund is suitable for the desired investment objectives.

DC plan participants who select from an available menu may have different investment objectives for their real asset allocation: diversification, inflation hedge, or growth hedge. DC plan sponsors can use RASA to help identify real asset funds to add to their menu and to better communicate with participants.

Defined contribution plan sponsors may want to select a real asset fund in their core menu that has performance different from a typical balanced stock-bond portfolio, *i.e.,* a **Diversification** strategy. Alternatively, they may select a fund which is muddled-focused with mediocre growth and inflation exposures.[20]

For the choice of a real asset fund in a target date fund the sponsor may wish to adopt a **Growth** strategy for younger participants and a **Growth Protection** strategy for participants nearing retirement.

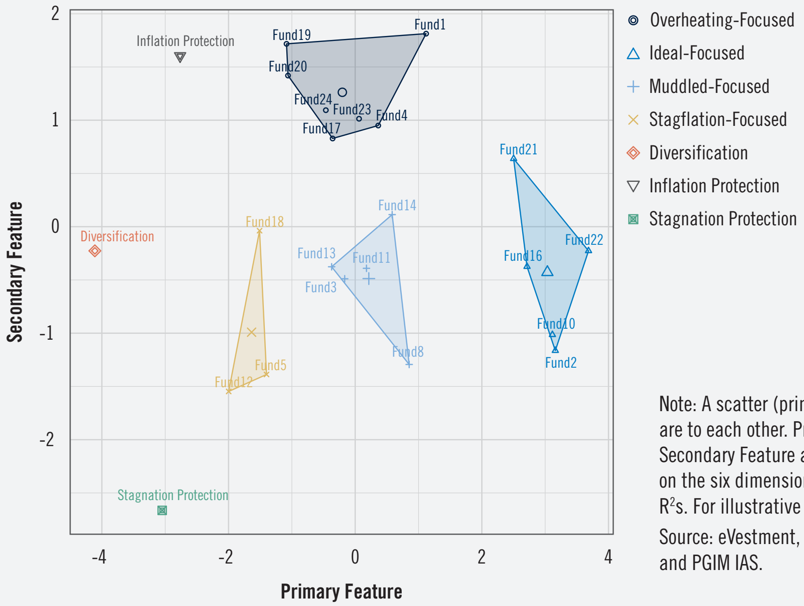
17 **Inflation Protection** – 33% commodity, 33% natural resource equities, and 33% MLPs; **Stagnation Protection** – 33% Gold, 33% MLPs, and 33% infrastructure debt; and **Diversification** – 33% Gold, 33% Commodities and 33% MLPs. We chose the three top/bottom real assets based on their CPI beta/CFNAI beta/R^2 rankings. We include only those public real assets considered in "The Diversity of Real Assets."

18 We also group funds using their simulated performance instead of RASA dimensions (see Appendix). Overall, the quality of clusters is better using the RASA dimensions to group funds. We use several clustering statistics (average Silhouette width, wb.ratio, and Calinski-Harabasz index) to measure the quality of the clustering solution.

19 For more details on the economic environment definitions and strategy portfolio performance, see "The Diversity of Real Assets."

20 Muddled is the most frequently occurring economic environment, 54% of the time. See "The Diversity of Real Assets."

Figure 10: Clustering Real Asset Funds Using Recent RASA Sensitivities



Note: A scatter (principal component) chart shows how close the 20 different funds are to each other. Primary Feature axis is the first principal component value and Secondary Feature axis is the second principal component value of 20 funds based on the six dimensions: 3m and 24m CPI and CFNAI betas and stock-bond regression R^2s. For illustrative purposes only.

Source: eVestment, Datastream, S&P Capital IQ, Federal Reserve Bank of Chicago, and PGIM IAS.

Figure 11: Average RASA Sensitivities by Cluster

	CPI 3m	CFNAI 3m	CPI 24m	CFNAI 24m	R^2 Stock/Bond 3m	Risk	Fund Count
Overheating-Focused	4.26	0.018	7.06	0.084	0.50	13.2%	7
Ideal-Focused	1.79	0.023	2.86	0.121	0.67	11.6%	5
Muddled-Focused	2.82	0.013	4.69	0.052	0.50	9.6%	5
Stagflation-Focused	3.22	0.007	5.33	0.005	0.30	8.4%	3
Diversification	*4.61*	*0.000*	*9.74*	*–0.049*	*0.14*	*11.8%*	*1*
Inflation Protection	*5.73*	*0.008*	*9.82*	*0.025*	*0.38*	*14.6%*	*1*
Stagnation Protection	*2.43*	*–0.008*	*6.37*	*–0.068*	*0.19*	*9.1%*	*1*

Note: For illustrative purposes only.

Source: eVestment, Datastream, S&P Capital IQ, Federal Reserve Bank of Chicago, and PGIM IAS.

Conclusion

CIOs have different investment objectives and need real asset portfolios that align well. There is a wide mix of real asset funds, which complicates fund selection or portfolio construction. While traditional analysis considers dimensions like performance, asset allocation and fund characteristics (such as investment objectives, benchmark, etc.) we show that fund and portfolio analysis can be enriched using RASA. Portfolios with similar asset class allocations may have different macroeconomic and market sensitivities which RASA can uncover.

Using RASA, investors can identify real asset funds and construct real asset portfolios that may be better aligned to their investment objectives.

Acknowledgments

We wish to thank Dr. Taimur Hyat for his valuable comments and suggestions.

APPENDIX

Benchmark Descriptions

Asset Class	Index Description	Source
Cash	S&P US Treasury Bill 0-3m Index	Datastream
Commodities	Bloomberg Commodity Index	Datastream
EM Equities	MSCI Emerging Market Index	Datastream
EM Hard Debt	Bloomberg Barclays EM USD Aggregate Index	Datastream
Foreign Currencies	Short US Dollar Index	Datastream
Global Bonds	Bloomberg Barclays Global Aggregate Index	Datastream
Global Equities	MSCI ACWI Index	Datastream
Global High Yield	Bloomberg Barclays Global High Yield Index	Datastream
Global TIPS	Bloomberg Barclays Global Inflation-Linked Index	Datastream
Gold	Gold Bullion LBM $/t oz	Datastream
Infrastructure Debt	S&P Brookfield Global Infrastructure ex MLP Corporate Bond Index	Datastream
Infrastructure Equities	MSCI ACWI Infrastructure Index (January 1999 - November 2001) and S&P Global Infrastructure Index (December 2001 - August 2019)	Datastream
Leveraged Loans	S&P Leveraged Loan Index	Datastream
MLP Debt	ICE BofAML US Pipeline Index	Datastream
MLPs	Alerian MLP Index	Datastream
Natural Resource Equities	MSCI ACWI Energy & Materials Index (cap-weighted)	Datastream
Pricing Power Equities	Top 20% of Russell 3000 with the highest profitability ratio (year-over-year change in EPS-to-sales ratio)	S&P Capital IQ
Real Estate Debt	Bloomberg Barclays Investment Grade CMBS Index (January 1999 - February 2000) and Bloomberg Barclays CMBS ERISA Eligible Index (March 2000 - August 2019)	Datastream
REITs	FTSE EPRA NAREIT Developed Index	Datastream
US Equities	S&P 500 Index	Datastream
US TIPS	Bloomberg Barclays US TIPS Index	Datastream

Clustering Methodology

We use the *hierarchical* clustering approach that begins by treating each asset as its own “cluster.” Then, the closest pair of clusters are combined based on the distance of their monthly returns from each other. (Distance is measured as the square root of the sum of the squared differences in monthly returns for each pair of assets. This is often referred to as the “Euclidean distance.”) We continue this process until only a single cluster remains. The optimal number of clusters is based on how close the objects in a cluster are to the other objects in the cluster, and how different that cluster is from other clusters.

As a robustness check to our hierarchical clustering approach we also used a k-means clustering approach. This latter approach suggests six clusters, with natural resources equities and EM Equities forming a single cluster. We use the Hartigan and Wong algorithm for partitioning.[21]

21 See Slonim N., E. Aharoni, and K. Crammer, “Hartigan’s k-Means Versus Lloyd’s k-Means – Is It Time for a Change?” *Proceedings of the Twenty-Third International Joint Conference on Artificial Intelligence*, August 2013.

Clustering Quality – Optimal Number of Asset-level Clusters

The Silhouette value for each object measures how close that object is to the other objects in its cluster, compared to objects in other clusters. The Silhouette value s_i for the i^{th} object is defined as

$$s_i = (b_i - a_i) / \max(a_i, b_i)$$

where ai is the average distance from the ith object to the other objects in the same cluster as i, and bi is the minimum average distance from the ith object to objects in a different cluster. The Silhouette value ranges from −1 to 1. A high Silhouette value indicates that i is well matched to its own cluster, and poorly matched to other clusters.

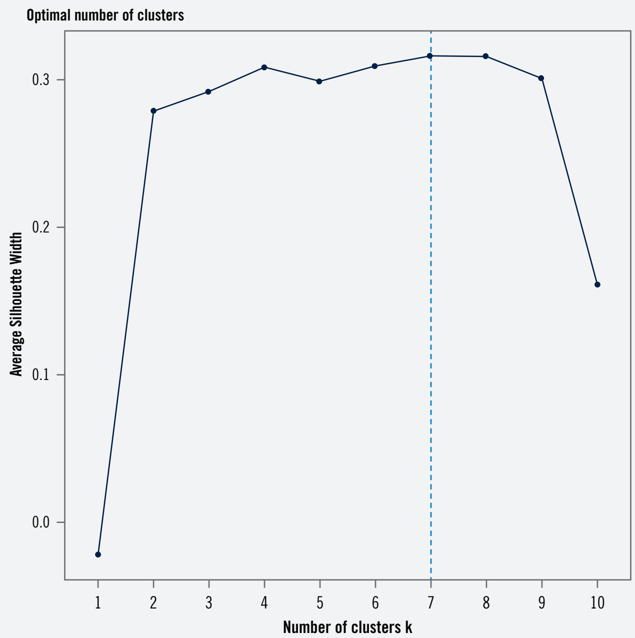
We determine the optimal number of clusters by examining the overall Silhouette value (S) which equals the average of the individual Silhouette values. A high Silhouette value suggests a good clustering solution.

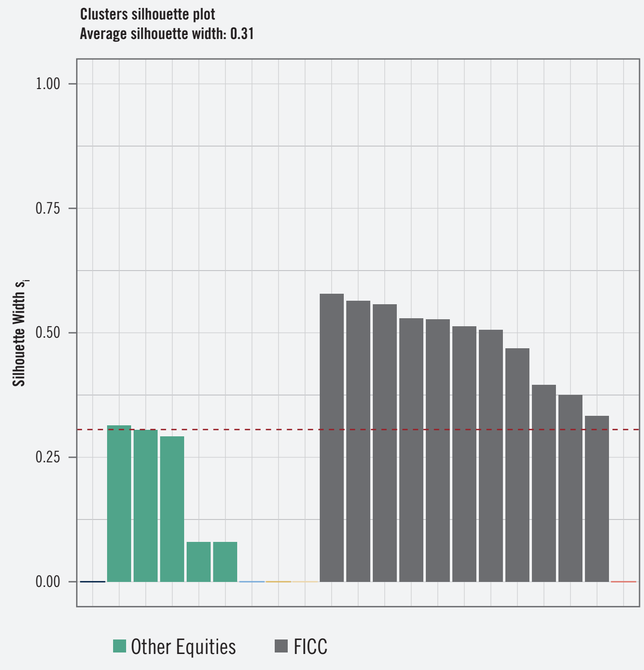
Robustness Checks for Sensitivity Estimates

The ranking of funds based on their performance in inflation/growth scenarios matches the ranking of the funds based on inflation/growth betas. We find that the rank correlations between fund CPI (3m) betas and quarterly fund performance when CPI is low (i.e., less than one-half standard deviation from the mean) was -0.99 and when CPI was high (i.e., greater than one-half standard deviation from the mean) was 0.86. Similarly, the rank correlations between fund CFNAI (3m) betas and quarterly fund performance when CFNAI is low was -0.91 and when CFNAI was high was 0.93.

We also observe that while, in aggregate, real asset fund volatility is moderate the variability in returns across high and low CPI quarters was much higher than, say, for the S&P 500. The variability in returns across high and low CFNAI quarters was lower than for the S&P 500.

Silhouette Scores for Asset-level Clusters





Note: For illustrative purposes only.

Source: Datastream, S&P Capital IQ, and PGIM IAS.

Variability in Fund 3m Performance by Low/High CPI/CFNAI
(USD returns; January 1999 – August 2019)

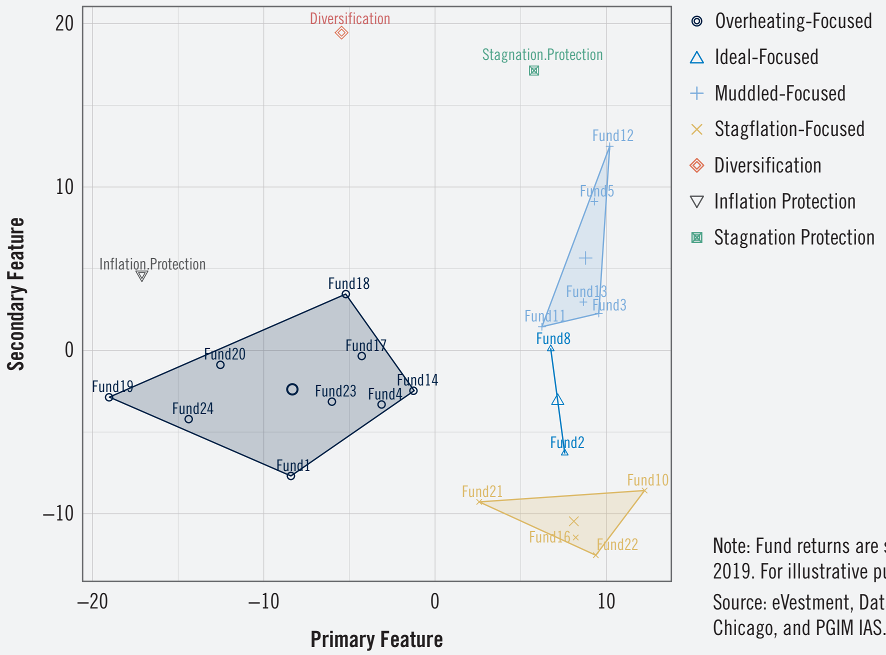
Funds	Beta (3m)				Fund Performance (CPI)					Fund Performance (CFNAI)				
	CPI	Rank	CFNAI	Rank	Low	Rank	High	Rank	Difference	Low	Rank	High	Rank	Difference
#1	4.3	3	0.025	3	–2.4%	17	5.1%	4	7.4%	–4.7%	20	3.2%	3	7.9%
#2	1.6	19	0.018	8	0.3%	4	2.8%	19	2.6%	–2.6%	9	2.5%	13	5.0%
#3	2.7	13	0.015	12	–1.0%	7	3.1%	17	4.1%	–2.3%	6	2.4%	15	4.6%
#4	3.6	8	0.020	5	–1.9%	13	4.6%	7	6.5%	–3.6%	17	2.8%	7	6.4%
#5	3.1	10	0.006	19	–1.7%	12	3.1%	18	4.8%	–1.3%	3	1.5%	20	2.8%
#8	2.5	16	0.008	18	–0.6%	5	3.4%	12	4.0%	–1.1%	2	2.2%	17	3.2%
#10	1.4	20	0.020	6	0.7%	1	2.8%	20	2.0%	–2.9%	11	2.8%	5	5.8%
#11	2.7	14	0.015	16	–1.0%	8	3.6%	11	4.6%	–2.2%	5	2.5%	12	4.7%
#12	2.8	12	0.005	20	–1.6%	10	3.2%	16	4.7%	–0.8%	1	1.5%	19	2.4%
#13	2.9	11	0.015	14	–1.2%	9	3.3%	14	4.5%	–2.3%	7	2.3%	16	4.7%
#14	3.3	9	0.015	15	–1.7%	11	4.2%	9	5.9%	–2.6%	8	2.5%	14	5.0%
#16	1.8	17	0.022	4	0.6%	2	3.3%	13	2.7%	–3.0%	12	3.1%	4	6.1%
#17	3.9	5	0.017	9	–2.4%	16	4.6%	6	6.9%	–3.1%	15	2.6%	11	5.7%
#18	3.7	7	0.009	17	–2.3%	15	4.3%	8	6.6%	–1.6%	4	2.1%	18	3.7%
#19	5.0	1	0.015	11	–3.5%	20	5.8%	1	9.3%	–3.0%	13	2.7%	9	5.6%
#20	4.7	2	0.016	10	–3.1%	19	5.3%	2	8.4%	–3.0%	14	2.6%	10	5.6%
#21	2.6	15	0.026	2	–0.8%	6	4.0%	10	4.8%	–4.3%	19	3.3%	2	7.6%
#22	1.6	18	0.027	1	0.5%	3	3.2%	15	2.7%	–4.2%	18	3.3%	1	7.5%
#23	3.9	6	0.019	7	–2.2%	14	4.7%	5	6.9%	–3.3%	16	2.8%	6	6.1%
#24	4.3	4	0.015	13	–2.6%	18	5.3%	3	7.9%	–2.6%	10	2.7%	8	5.3%
S&P 500	0.8		0.030		1.1%		2.6%		1.5%	–4.8%		3.2%		7.9%
Treasury 10y	–1.7		–0.003		0.6%		1.3%		0.7%	1.2%		0.3%		–0.9%
Correlation						–0.99		0.86			–0.91		0.93	

Note: For illustrative purposes only.

Source: eVestment, Datastream, S&P Capital IQ, Federal Reserve Bank of Chicago, and PGIM IAS.

Comparing Fund Cluster Approaches (Simulated Fund Returns *vs.* RASA Dimensions)

Clustering Real Asset Funds Using Simulated Fund Returns



Note: Fund returns are simulated for the period from January 1999 to August 2019. For illustrative purposes only.

Source: eVestment, Datastream, S&P Capital IQ, Federal Reserve Bank of Chicago, and PGIM IAS.

Fund Clusters (Using Simulated Fund Returns) Average RASA Dimensions and Risk

	CPI 3m	CFNAI 3m	CPI 24m	CFNAI 24m	R^2 Stock/Bond 3m	Risk	Fund Count
Overheating-Focused	4.09	0.017	6.78	0.077	0.50	12.6%	9
Ideal-Focused	1.85	0.024	3.07	0.128	0.65	12.0%	4
Muddled-Focused	2.04	0.013	2.53	0.067	0.68	9.2%	2
Stagflation-Focused	2.84	0.011	4.96	0.026	0.38	8.7%	5
Diversification	4.61	0.000	9.74	−0.049	0.14	11.8%	1
Inflation Protection	5.73	0.008	9.82	0.025	0.38	14.6%	1
Stagnation Protection	2.43	−0.008	6.37	−0.068	0.19	9.1%	1

Note: For illustrative purposes only.

Source: eVestment, Datastream, S&P Capital IQ, Federal Reserve Bank of Chicago, and PGIM IAS.

Comparing Fund Cluster Approaches

Clustering Statistics	RASA	Simulated Fund Returns
Avg. Silhouette width	0.35	0.26
Dunn2	1.5	1.3
wb.ratio	0.36	0.52
CH Index	21.3	8.5

Note: For illustrative purposes only.

Source: eVestment, Datastream, S&P Capital IQ, Federal Reserve Bank of Chicago, and PGIM IAS.

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