Active vs. Passive Asset Management:
An Update

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1 | INTRODUCTION

In this latest release of the Active vs Passive Management research, we have updated previous results on Morningstar category classification into "active" or "passive." We first carry out estimations using the entire available data history (for some categories the data start in 1980s), which therefore give us results that hold on average across the whole time period. Second, we produce time trend estimates, which zero in on a particular time period.

Our findings show that when using the entire data history for equity asset classes, the active or passive designations remained largely consistent with the previous study. With the exception of large cap growth, the data suggest that domestic large cap asset classes may be passively managed, whereas satellite asset classes (particularly domestic and foreign small cap) could be managed by selecting active managers. Similarly, fixed income asset class designations remained unchanged, with passive management suggested for most categories.

Our time trend (or latest period) analysis examines four decades of available performance figures and extracts only the most recent three year data at a particular point, with interesting results. For example, even though the large cap growth asset class is designated as active when looking at the average results over the full time period, recent trends suggest that active managers in that category have had difficulty outperforming.

2 | METHODOLOGY

2.1 | Overview

The motivation for using Active vs. Passive methodology for portfolio implementation is straightforward: it is a much easier task to select active managers that add positive alpha[1] from an asset class, where the proportion of such managers is high. This contrasts with identifying a positive alpha manager through the "needle in a haystack" approach in an asset class where this proportion is small. This is especially true if an investor or advisor has not demonstrated an ability to select managers with positive future risk-adjusted returns to begin with.

Additionally, as in earlier versions of this research, we have assigned an "active," "passive," and "neutral" moniker to an asset class or a category based on a proportion of positive alpha managers in the peer group (more on this in the next section). However, our cut-offs for these three classifications, although reasonable and defensible, are necessarily arbitrary. That is, what might be an acceptable proportion of positive alpha managers for one investor or advisor to pursue an active strategy in a particular category might seem altogether too low and risky for another. Thus, investors and advisors should consider their unique circumstances and use the calculated proportions of each category's positive and negative alpha managers as a guide for classifying the categories into "active," "passive," and "neutral."

Active or Passive Classification

This section describes how we calculate the proportion of a category's positive and negative alpha managers. We also, describe a heuristic rule that we employ for those calculated proportions to decide whether a particular category is "active," "passive," or "neutral."

Skilled Managers:
Those whose alpha is above or equal to a statistically significant positive percentile, calculated from ranking all the managers in the peergroup.

Unskilled Managers:
Those whose alpha is below or equal to a statistically significant negative percentile, calculated from ranking all the managers in the peergroup.

Alpha:

Also known as risk-adjusted return, is equal to the difference between the performance of the manager (MP) and the benchmark (BP), with the benchmark multiplied by the manager's beta.

The formula is: A=MP–BP*beta.

First, we measure the statistical significance (positive and negative) for each percentile of the cross-sectional alpha distribution for all mutual funds (both dead and alive) in the Morningstar database (see Table 1) from January 1980 to April 2022. We use regression analysis to calculate manager alphas, employing all the available data for that manager and using the benchmark for the manager's Morningstar category as the independent variable, to determine the "manager success rate" and the "manager failure rate."

We then classify a category as "active" if the lowest statistically significant positive percentile was at 67 or below. In other words, an active manager's success rate is at least one-third, meaning at least one-third of a distribution of alphas in a given category are statistically positive. We classify a category as "passive" if the manager failure rate is at least two-thirds, with the highest statistically negative percentile for a passive category at 67 or above, meaning that at least two-thirds of a distribution of alphas in a given category are statistically negative. We classify a category as "neutral" if it is neither active nor passive. Further, managers with an alpha above or equal to a statistically significant positive percentile are denoted as "skilled," whereas managers are considered to be "unskilled" if they have an alpha below or equal to a statistically significant negative percentile. Thus, each Morningstar category is divided into a group of skilled, unskilled, and indeterminate managers.

Note that we grouped all the managers from the same category in the same peer group, regardless of the time that they were active, and the results show the average proportion of active managers for a particular category across time.

2.2 | Time Dimension Of Active or Passive Classification

During our more than four-decade long study period, managers had vastly different market environments, asset management approaches, and technologies available to them. Changes in these factors can produce markedly different proportions of managers generating positive alpha over time. In fact, as we will see later when discussing the time trends of active management, these results can, and most likely should, be used in making the active or passive investment decision.

Our trend analysis measures performance over rolling periods at monthly intervals, where at any given month we analyze only those managers who are alive at that particular time period. Also, we use 36 months of data for the alpha regression analysis. To be consistent with whole-sample analysis, we measure all managers against their Morningstar category benchmarks. This gives us a time series at monthly frequency of the proportions of positive alpha managers in a particular category, and we repeat this analysis across all of the categories. We apply the same estimation methodology as we used in the whole-sample analysis to determine whether a particular positive or negative percentile is statistically significant.

Regression analysis:

A statistical method to obtain a linear explanatory relationship between a particular variable ("dependent variable") and a set of potential explanatory variables ("independent variables").

Whole Sample Analysis:

Refers to using all the available historical data, when running a regression analysis for a particular manager. Since this approach uses the maximum available data, it may provide analysis that is less relevant for more recent periods, since the results are influenced by the whole available, and potentially distant, history.

Manager Failure Rate:

The proportion of managers whose alpha is below or equal to a statistically significant negative percentile, calculated from ranking all the managers in the peergroup.

Manager Success Rate:

The proportion of managers whose alpha is above or equal to a statistically significant positive percentile, calculated from ranking all the managers in the peergroup.

3 | RESULTS

3.1 | The Universe

Our study covers the entire Morningstar Open End Fund (i.e., Mutual Fund) universe as of April 2018. Table 1 shows that this universe (both dead and alive funds) has grown since we published the previous version of this research four years ago. In particular, not only has the number of managers increased (from slightly fewer than 12,000 five years ago to almost 13,000 now), but also the number of Morningstar categories has risen (from 113 to 129). As before, we exclude some categories such as commodities precious metals, consumer defensive, miscellaneous sector, trading-inverse/trading-leveraged, and trading-miscellaneous, as the number of managers in those categories is too small to obtain statistically meaningful and valid results.

Table 1

Description of the universe used in the study.

	Apr-2018	Apr-2022
NUMBER OF FUNDS	**11831**	**12757**
Alive	6471	6116
Dead	5360	6641
NUMBER OF MORNINGSTAR CATEGORIES	**113**	**129**
Included	102	114
Excluded	11	15
TIME PERIOD	**Jan 1980 - Apr 2018**	**Jan 1980 - Mar 2022**
Number of Months	468	507
Earliest Category Start	Jan-1980	Jan-1980
Latest Category Start	Apr-2014	Aug-2017

3.2 | Active or Passive Classification Based on Entire Data History

Although we note significant trends in the proportions of positive and negative alpha managers in various categories through time (more on this in section 3.3), the proportion estimates based on the entire data history have not shown significant changes.[2] This is because the entire data sample spans more than 40 years, as highlighted in Table 1, whereas we have added only four years of data since the last study.

Even so, certain Morningstar categories experienced meaningful changes in the percentile of positive and negative alpha active managers (see Table 2 for details). For example, the proportion of positive alpha managers in the Foreign SMid Core category based on the entire data history significantly decreased over these last four years (34% currently versus 74% four years ago). Other categories that included meaningful changes in the proportion of positive alpha active managers, when the whole data history is used, include Foreign SMID Value and Commodities.

Some changes highlighted above have resulted in a change in the "active," "passive," and "neutral" moniker assigned to the category (see Table 2 for details). In particular, Commodities category has moved from "passive" to "active." Also, Large Cap Value has moved from "passive" to "neutral." The rest of the category switches (Emerging Market Bond, Intermediate Bond, and MidCap Core) are from "neutral" to "passive."

"Time-trend" Analysis:
We iteratively walk through the four decades of available data and at every time period use only the most recent data (most recent 3 years at that particular point in time) to analyze manager performance. Unlike whole sample analysis, trend analysis, implemented by applying regression analysis over rolling periods, ignores distant past data and focuses only on the most recent data.

MORNINGSTAR CATEGORY	Apr-2018			Mar-2022			
	Mgr. failure rate (avg.)	Mgr. success rate (avg.)	Type (avg.)	Mgr. failure rate (avg.)	Mgr. success rate (avg.)	Type (avg.)	Category switch
Emerging Markets	51	44	A	51	39	A	N
Foreign LCG	46	44	A	42	47	A	N
Foreign LCV	44	39	A	42	44	A	N
Foreign S/M C	11	74	A	41	34	A	N
Foreign S/M G	15	75	A	6	87	A	N
Foreign S/M V	19	57	A	37	36	A	N
Large Cap Growth	53	39	A	59	34	A	N
Mid Cap Growth	56	36	A	56	33	A	N
Small Cap Core	35	52	A	38	54	A	N
Small Cap Growth	28	64	A	26	66	A	N
Small Cap Value	39	45	A	39	44	A	N
Real Estate	39	43	A	39	40	A	N
Commodities	77	11	P	32	38	A	Y
Large Cap Value	69	26	P	64	28	N	Y
Foreign LCC	56	32	N	59	32	N	N
High Yield	61	31	N	63	27	N	N
Emerging Markets Bond	62	28	N	67	18	P	Y
Bank Loan	68	16	P	78	9	P	N
TIPS	74	17	P	69	16	P	N
IT Bond (Intermediate Core Bond)	63	29	N	72	18	P	Y
Muni Nat'l Int.	88	9	P	82	9	P	N
Muni Nat'l L	84	7	P	86	8	P	N
Muni Nat'l S	84	9	P	80	14	P	N
Large Cap Core	72	20	P	74	21	P	N
Mid Cap Value	67	24	P	67	21	P	N
Mid Cap Core	65	25	N	68	21	P	Y

Table 2

Categorization of asset classes into "Active" (A), "Passive" (P), and "Neutral" (N), using the entire available history of manager returns.

Active:

Manager Success Rate ≥ 33

Neutral:

Manager Success Rate < 33 & Manager Failure Rate < 67

Passive:

Manager Failure Rate ≥ 67

Recall we stated earlier that the cut-offs that we use for assigning the "active," "passive," or "neutral" moniker to categories are somewhat arbitrary, and we advise investors and advisors to consider their approach to investment analysis, combined with the underlying percentile of positive alpha active managers that we have provided, to decide whether to implement a category with active or passive products.

3.3 | Active or Passive Classification Through Time

As noted in section 3.2, our initial analysis of the proportion of positive alpha managers in each category was based on averaging manager returns across the entire time period. Thus, the results are an average of these proportions over time, and although they are useful in summarizing the results, they necessarily gloss over the trends that exist in these proportions across time. Importantly, the results might not give us an up-to-date picture of the latest category trends. In this section we discuss the results of time-trend analysis of the proportion of positive alpha managers, using the methodology described in section 2.3.

Table 3 shows the results for time-trend analysis, a key component of our updated research in this white-paper, which presents a current snapshot of the positive and negative alpha manager proportions in their respective categories. In particular columns four and five (denoted by "CUR" for "current") give the most recent values, based on rolling-period analysis, for manager failure/success rates (MFR/MSR). For ease of reference, we also have listed the latest average results from Table 2 in columns one through three (denoted by "AVG"). The "Potential Change" column in Table 3 (column six) uses the criteria from the time-average results (see section 2.2 as well as Table 2) to indicate what the "active," "passive," or "neutral" moniker would be when using the most recent time results (columns four and five).

In the last six columns we present the change in the proportion of positive and negative alpha managers based on evaluating only the currently alive managers' most recent three-, five-, and ten-year intervals for all the categories in our study. These columns highlight the dynamics of changes in the positive/negative alpha manager proportions through time. For example, to calculate the proportion of positive alpha managers three years ago in, say, the Large Cap Growth category, we would take the current value for this category (9) and subtract the 3-year change in the positive alpha managers (-17), giving us the proportion of 26. Thus, the LCG category has experienced significant decrease in the positive alpha manager proportion (26 to the current 9 percent) over the last three years. Logically, the proportion of negative alpha managers for this category has experienced similar-size increase (19 percent), which means that three years ago the negative alpha manager proportion in Large Cap Growth was about 64 percent (83 - 19).

The current value of the positive/negative manager alpha proportions along with their time trends give us powerful insights into the past dynamics of these variables, which could inform our future estimates for these values.

Using the most recent time period, rather than the time-average results, sheds additional light on the latest performance of active managers in a particular category. As presented in Table 3, classifications based on the most recent time-trend analysis would result in switching the "active," "passive," or "neutral" moniker in half the categories in Table 2—those built on time-average results. This highlights fairly significant changes in the proportion of the positive and negative alpha managers through time in multiple categories. These results are reinforced by complementing them with the recent trend information given in the last six columns of Table 3. This analysis reveals, for example, that active managers in domestic Small Cap category have

MORNINGSTAR CATEGORY	Mgr. failure rate (avg.)	Mgr. success rate (avg.)	Type (avg.)	Mgr. failure rate (curren)	Mgr. success rate (curren)	Potential switch	3-year change Mgr. failure rate (current)	3-year change Mgr. success rate (current)	5-year change Mgr. failure rate (current)	5-year change Mgr. success rate (current)	10-year change Mgr. failure rate (current)	10-year change Mgr. success rate (current)
COMMODITIES	32	38	A	4	55	–	–35	15	–28	–3	–6	7
Emerging Markets	51	39	A	36	49	–	–22	25	–10	5	–5	–1
FOREIGN LCG	42	47	A	39	47	–	0	6	3	–2	2	4
FOREIGN LCV	42	44	A	19	65	–	–45	53	–16	20	–36	38
FOREIGN S/M C	41	34	A	24	47	–	–26	12	–1	–1	13	–33
FOREIGN S/M G	6	87	A	26	42	–	16	–17	9	–10	13	–21
FOREIGN S/M V	37	36	A	6	69	–	–19	22	–3	25	–32	31
Large Cap Growth	59	34	A	83	9	P	19	–17	1	–3	–1	0
Mid Cap Growth	56	33	A	28	62	–	–28	27	–30	39	–35	33
Small Cap Core	38	54	A	25	69	–	–47	46	–18	30	1	4
Small Cap Growth	26	66	A	1	88	–	–22	27	–48	52	–31	28
Small Cap Value	39	44	A	32	54	–	–40	39	–19	20	31	–33
REAL ESTATE	39	40	A	16	68	–	–14	21	–29	25	–39	62
FOREIGN LCC	59	32	**N**	47	43	A	–21	24	22	–19	–6	4
High Yield	63	27	**N**	46	46	A	–20	22	–10	14	–18	22
Large Cap Value	64	28	**N**	31	59	A	–19	20	–33	33	–24	22
BANK LOAN	78	9	P	80	4	–	–2	–2	14	–15	36	–42
EM BOND	67	18	P	38	45	A	–11	8	–50	42	–25	36
INTER TERM BOND	72	18	P	39	50	A	–5	11	–6	16	18	–22
Large Cap Core	74	21	P	66	25	–	–3	2	–10	8	–11	10
Mid Cap Core	68	21	P	60	29	N	–1	3	–7	5	–16	13
Mid Cap Value	67	21	P	45	42	A	–6	11	–24	17	–25	32
MUNI NAT'L INT.	82	9	P	49	36	A	–21	24	–18	19	–12	14
MUNI NAT'L L	86	8	P	52	36	A	–6	3	31	–20	13	0
MUNI NAT'L S	80	14	P	51	23	N	–14	8	–13	–3	10	–14
TIPS	69	16	P	37	37	A	–4	18	–44	33	4	–10

made considerable improvements in their ability to deliver alpha over the last three years. On the other hand, domestic Large Cap Growth category has experienced one of the largest declines in the proportion of positive alpha managers over the last three years. In fact, their current positive alpha manager proportion is only 9 percent.

These results make intuitive sense, as , excluding the most recent market downturn, Growth stocks have done exceedingly well, which makes it more difficult for managers to outperform passive benchmarks.

4 | BEYOND BETA

The preceding results focused on alpha adjusted for one factor, market exposure, by including a modification of benchmark performance to account for each manager's beta, or the strength of its exposure to the relevant market or asset class. But beta is not the only component of the total return equation, and not all return earned over the benchmark is the result of idiosyncratic skill. Many other factors earn a risk premia as well. Reams of academic studies have focused in particular on rewarded style factors such as value, small size, momentum, quality and low volatility. Please refer to our whitepaper, The Impact of Strategic Beta on the Managed Product Landscape, for a review of these studies.

Given our knowledge of these persistent sources of excess return, we are left to ask - are managers that show alpha adjusted only for market risk through beta really adding unique skill to earn their excess return, or are they simply earning the return from exposure to these well-researched rewarded risk factors?

4.1 | TRUE SKILL

Traditional active strategies have long benefited from these known risk premia through their idiosyncratic stock selection. Strategies that look for undervalued, high quality stocks or stocks with persistent earnings surprises are prime examples that naturally lead to overexposure to the risk factors that have historically earned a premium, like value, quality and momentum in these examples. Any excess return they earn consists of the premia from these biases along with any true skill the manager possessed. In the past, the entirety of this return over the market was referred to as alpha (Figure 1), but the desire to delineate the true skill and risk premia components of excess return has grown stronger as cost compression pervades the industry.

Figure 1

Advances in financial research, big data and computing ability have advanced our understanding of excess return. We now recognize that some of the excess return that used to be called "alpha" is actually earned through exposure to systemically present risk factors.
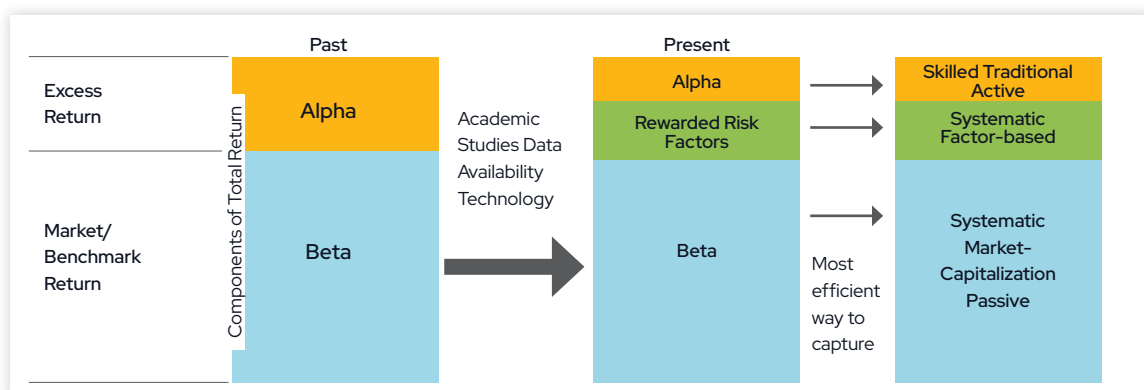
While investors had little choice but to pay active management fees to tilt toward factors in the past, the landscape has evolved. Systematic strategies that target the common asset classification schemes of value and small size have been staples of the investment landscape for decades. Today, the universe of cost effective, systematic strategies that target other rewarded risk premia is ever-expanding. The right-hand side of Exhibit 1 shows the philosophies that most efficiently capture the various sources of expected return. Efficiency in this sense refers to the strongest exposure to these sources for the lowest cost.

In nearly any asset class, these less costly systematic factor-based strategies can be used to decouple rewarded risk factors from more expensive true manager alpha. Because investors now have choice in how they access factor returns, they are no longer tied to paying an active manager for them. A combination of systematic factor-based strategies and skilled traditional active strategies can lead to more cost-effective excess return. The onus is on active managers to earn their higher fee by contributing unique skill over and above factor premia, and the way to measure this true skill is by looking at multifactor-adjusted alpha.

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4.2 | FACTOR ADJUSTMENTS

Almost as soon as the one-factor CAPM was proposed, researchers began amassing evidence to extend it to multiple factors, recognizing that market exposure alone did not fully explain return. The academic research of the last half century or so has produced solid evidence that the value, momentum, quality, small size and low volatility factors have been rewarded with excess risk-adjusted return over time, and incorporating these factors into modeling exercises has proven more accurate in forecasting risk than the one factor market model.

Recognizing that these systematic sources of excess return exist, we can write a regression equation to account for them and paint a clearer picture of true idiosyncratic alpha as a measure of manager skill. A regression approach allows us to bucket total return into systematic factors, like beta and style factors, and alpha, a measure of total return over and above what is captured with systematic sources of return.

A representative equation for a time series regression to assess this skill is as follows:

$$R_{it} = \underbrace{a_i}_{\text{Skill}} + RF_t + Bi(R_{Mt}-R_{Ft}) + \underbrace{b_{qi}(qual_t) + b_{mi}(mom_t) + b_{si}(size_t) + b_{li}(lowvol_t) + b_{vi}(value_t)}_{\text{Systematic risk factors}} + e$$

In this equation, ai is alpha, or the return not attributable to systematic risk factors. Rit is the return on a security or portfolio i for period t, RFt is the risk free return, and RMt is the return on a market capitalization-weighted market portfolio. The factor premia quality, momentum, size, low volatility and value are represented by their respective abbreviations, and the exposure of the security or portfolio to each of these factors is represented by their betas (bqi, bmi, bsi, bli, bvi). e represents a residual term assumed to have a mean of zero. Some statistical testing on the output of this equation will help identify a truly skilled manager as one that shows statistically significant alpha, and can flag those that have only added excess return with factor tilts or luck.

This same approach can be used to evaluate the profile of systematic factor-based strategies. Where it would be used to look for statistically significant alpha of traditional active strategies, the focus for factor strategies is on the strength of exposure to targeted factors. However, assessing these strategies is complicated, because different measures of even a single factor versus that same factor's style benchmark will give different answers as to whether a strategy had more or less factor versus idiosyncratic risk or alpha driving its return profile. For example, if we measure a price-to-book based value strategy against a value benchmark denominated by price-to-earnings and price-to-sales, the strategy may show idiosyncratic return that is really factor alpha in disguise. Similar problems arise if the strategy and benchmark chose different weighting schemes, market capitalization-weighted versus equal-weighted versus signal-weighted, for example. Evaluation of factor-based strategies is clearly a nuanced exercise.

5 | SUMMARY

This version of the Active vs. Passive whitepaper, updating the previous results in two takeaways.

- First, when we examined the entire data history, we found that the "active," "passive," and "neutral" asset class categorizations changed little from previous versions of the whitepaper.

- Second, we introduced time-trend, rolling-three-years analysis to measure the positive and negative alpha manager proportions in a peer group, concluding that these proportions can change meaningfully over time. Investors and advisors contemplating using active or passive implementation vehicles can use this analysis for a current perspective on the proportion of positive and negative alpha managers in a category, combined with other data points, to make a more informed investment decision.

5.1 | ACTIVE-PASSIVE 2.0

As part of a due diligence mosaic, traditional active strategies and systematic factor-based strategies can be evaluated using an approach like the one presented in section 4.2. In aggregate, this type of factor-adjusted analysis could also improve our understanding of which asset classes have a higher proportion of truly skilled managers.

Future versions of this study will attempt to build upon our existing research by evaluating two central questions. First, how do we assess the success of systematic factor-based strategies that attempt to capture factors that academic research has shown have the ability to outperform over time across asset classes? The ActivePassive study, while good at identifying success from idiosyncratic strategies, does not attempt to make a judgement about systematic strategies that seek to quantitatively capture rewarded risk factors. These strategies may show up as successful or unsuccessful in any given iteration of our study based on the performance of the style factors they seek to capture during that period.

The second question that arises from a consideration of factor-based research is in which asset classes are investors most likely to find actively managed strategies with broad factor-adjusted alpha, not just beta-adjusted alpha? No one wants to overpay for risk premia.

We will build upon the framework presented here in an effort to answer these questions. While no simple exercise, we expect the outcome of this future research to provide significant new insights into both alpha-seeking and factor-based investment products.

Notes

1. Note that in this study we equate a manager's alpha (i.e., risk-adjusted return) with his skill. This, of course, does not need to be the case, as conditions beyond the manager's control (e.g., fund's size) may limit a potentially skilled manager's ability to produce a positive risk-adjusted return (see, for example, Berk & Green 2004 and Berk 2005). Still, a manager who might be skilled, but unable to deliver a positive risk-adjusted return due to some external constraints, is observationally equivalent to an unskilled manager, so in this study we treat these two groups as being equal. Also important, a manager might be able to deliver positive gross (i.e., before expenses) alpha, whereas the manager's net (i.e., after expenses) alpha might be negative. All our results are net of expenses, so our evaluation of whether a manager is skilled or not is necessarily related to the expenses that the manager charges.

2. In this section we describe the results of applying the methodology described in sections 2.1 and 2.2.

3. The Appendix contains the plots of the time trends of proportions of positive and negative alpha managers for all the categories that we have analyzed.

4. This viewpoint also was echoed recently by Morningstar's John Rekenthaler (https://www.morningstar.com/articles/902951/intermediateterm-bond-managers-pull-ahead.html).

5. The regression here refers to a linear OLS regression of a manager's current net returns against current performance of the manager's benchmark.

6. The point of the confidence intervals is to denote all the other likely values of an estimate. Confidence intervals, in addition to the estimate itself, are helpful for understanding the precision of the estimate. The more volatile the data, the less precise the estimate (i.e., the wider the confidence interval).

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Disclosure:

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