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Active vs. Passive Asset Management: A Revisit and Further Research

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1 | INTRODUCTION

We have updated our Active vs. Passive Asset Management research and refreshed the findings of the prior version of the whitepaper to accomplish three goals. First, we designate particular Morningstar categories as candidates for either active or passive management by measuring the statistical significance of every percentile of distribution of alphas in each category. We combine nearly four decades worth of data to arrive at the final positive and negative risk-adjusted return proportions for a peer group and provide average results across time. Second, we introduce "time-trend" analysis, yielding insights as to how the proportion of "skilled" and "unskilled" managers in a category changes over time. Finally, we incorporate artificial intelligence in the form of a machine-learning model in an effort to provide guidance as to what dimensions may prove to be most useful for predicting of future outperformance.

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.

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. Finally, our machine-learning model indicates the potential for positive out-of-sample results for portfolios constructed based on certain dimensions, such as low expense ratio.

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.

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.

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."

2.2 | 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."

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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 2018. 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.

2.3 | Time Dimension Of Active or Passive Classification

During our four-decade 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.

2.4 | Future Performance Prediction: Machine Learning to the Rescue

We utilized machine-learning techniques when we updated our research to help us uncover nonlinear relationships between risk-adjusted returns and various potential drivers. In particular, we use a machine-learning technique called "Generalized Additive Models" (GAM) to understand the relationship between future risk-adjusted returns of active managers and the drivers that could affect these returns, such as past performance, expense ratio, fund size, turnover, etc. GAM relies on an estimation algorithm, "the machine," to uncover and quantify (or learn) the nature of those relationships, rather than following traditional linear regression to determine them.

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 considerably since we published the previous version of this research five years ago. In particular, not only has the number of managers increased (from slightly fewer than 10,000 five years ago to almost 12,000 now), but also the number of Morningstar categories has risen (from 92 to 113). 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.

	May-2013	Apr-2018
NUMBER OF FUNDS	**9701**	**11831**
Alive	5581	6471
Dead	4120	5360
NUMBER OF MORNINGSTAR CATEGORIES	**92**	**113**
Included	75	102
Excluded	17	11
TIME PERIOD	**Jan 1980 - May 2013**	**Jan 1980 - Apr 2018**
Number of Months	401	468
Earliest Category Start	Jan-1990	Jan-2001
Latest Category Start	Apr-2007	Apr-2014

3.2 | Active or Passive Classification Based on Entire Data History

"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.

Although we note significant trends in the proportions of positive and negative alpha managers in various categories through time (more on this in section 3.4), the proportion estimates based on the entire data history have not shown significant changes.[2] This is because the entire data sample spans nearly 40 years, as highlighted in Table 1, whereas we have added only five 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 real estate category based on the entire data history significantly increased over these last five years (43% currently versus 33% five 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 large cap value, foreign small cap value, emerging markets bonds, mid cap core, foreign large cap core, and bank loans.

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, foreign large cap value has moved from "neutral" to "active." Also, foreign large cap core has moved from "active" to "neutral."

MORNINGSTAR CATEGORY	May-2013 MGR. FAILURE RATE (AVG.)	May-2013 MGR. SUCCESS RATE (AVG.)	May-2013 TYPE	Apr-2018 MGR. FAILURE RATE (AVG.)	Apr-2018 MGR. SUCCESS RATE (AVG.)	Apr-2018 TYPE	CATEGORY SWITCH
Emerging Markets	48	39	A	51	44	A	N
Foreign LCG	50	41	A	46	44	A	N
Foreign LCV	56	32	N	44	39	A	Y
Foreign S/M C	12	80	A	11	74	A	N
Foreign S/M G	5	76	A	15	75	A	N
Foreign S/M V	5	74	A	19	57	A	N
Large Cap Growth	49	46	A	53	39	A	N
Mid Cap Growth	53	36	A	56	36	A	N
Small Cap Core	32	56	A	35	52	A	N
Small Cap Growth	26	63	A	28	64	A	N
Small Cap Value	36	42	A	39	45	A	N
Real Estate	54	33	A	39	43	A	N
EM Bond	53	14	N	62	28	N	N
Foreign LCC	66	34	A	56	32	N	Y
High Yield	59	28	N	61	31	N	N
Mid Cap Core	56	31	N	65	25	N	N
Bank Loan	73	8	P	68	16	P	N
TIPS	69	15	P	74	17	P	N
IT Bond	67	34	P	63	29	P	N
Muni Nat'l Int.	90	0	P	88	9	P	N
Muni Nat'l L	85	6	P	84	7	P	N
Muni Nat'l S	90	6	P	84	9	P	N
Large Cap Core	68	25	P	72	20	P	N
Large Cap Value	69	25	P	69	26	P	N
Mid Cap Value	69	21	P	67	24	P	N
Commodities	--	--	--	77	11	P	--

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

However, these changes are mostly because the proportion of positive alpha active managers for these two categories fluctuates around 33%, which is the cut-off that we use for classifying a category as "active." 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 | Characteristics of Active and Passive Managers

In analyzing the properties of skilled and unskilled groups of managers, we observe basically the same results as last time (see Table 3). First, expense ratios are uniformly lower for the skilled group compared with the unskilled group. Importantly, compared with our study five years ago, the expenses of the skilled group have decreased almost uniformly across the categories (domestic fixed income being the rare exception, with the median expense ratio for the skilled group increasing from 71 to 72 basis points). The international equity and domestic value categories have the highest expense ratios in the skilled group. On the other hand, with the exception of a slight decrease in expense ratios in the international equity categories, the unskilled group generally has the same or an even higher level of expenses.

Second, as in the previous version of our research, portfolio turnover for domestic and international equity categories is uniformly lower for the skilled group compared with the unskilled group. This observation also extends to other categories. We hypothesize that this effect is due to higher trading costs associated with higher turnover, which leads to lower alpha, everything else remaining constant.

Although these results do not indicate the direction of causality (i.e., do good managers tend to charge lower fees in addition to having great investment insights, or are managers good—where "good" means positive, after-fee alpha—because they charge lower fees?), our machine-learning techniques show that, in fact, expense ratio is one of the most important factors in forecasting positive future net alphas.

Table 3

Description of characteristics of "Skilled" (S) and "Unskilled" (U) managers along various dimensions.

	EXPENSE RATIO				TURNOVER				BETA				CAPTURE RATIO			
	May-2013		Apr-2018		May-2013		Apr-2018		May-2013		Apr-2018		May-2013		Apr-2018	
CATEGORY GROUP	U	S	U	S	U	S	U	S	U	S	U	S	U	S	U	S
OVERALL	1.13	0.96	1.22	1.00	62	69	61	52	1.00	0.76	0.88	0.82	0.90	1.00	0.86	1.04
DOM. EQ.	1.30	1.22	1.30	1.18	68	53	69	49	0.95	0.91	0.98	0.94	0.88	1.04	0.87	1.02
DOM. EQ. C	1.29	1.19	1.30	1.19	70	48	67	49	0.95	0.90	0.98	0.92	0.87	1.03	0.84	0.99
DOM. EQ. G	1.36	1.23	1.37	1.21	82	69	82	58	0.93	0.93	0.97	0.95	0.89	1.06	0.91	1.07
DOM. EQ. V	1.26	1.23	1.28	1.12	53	43	56	44	0.96	0.90	0.97	0.93	0.88	1.03	0.86	1.01
DOM. EQ. L	1.21	1.12	1.23	1.09	60	45	59	42	0.96	0.93	0.97	0.93	0.88	1.01	0.88	1.01
DOM. EQ. M	1.34	1.21	1.35	1.16	74	60	65	53	0.95	0.91	0.96	0.91	0.88	1.04	0.87	1.02
DOM. EQ. S	1.35	1.32	1.36	1.27	72	54	80	57	0.94	0.89	0.98	0.95	0.89	1.06	0.87	1.03
INT'L EQ.	1.50	1.38	1.46	1.22	65	38	64	41	1.00	0.97	0.96	0.94	0.86	1.09	0.93	1.12
INT'L EQ. L	1.41	1.32	1.36	1.03	64	36	55	32	0.98	0.96	0.98	0.94	0.89	1.06	0.93	1.11
INT'L EQ. M/S	1.50	1.37	1.56	1.36	60	36	76	48	1.03	1.00	0.94	0.94	0.81	1.14	0.92	1.15
DOM. FIXED	0.98	0.71	1.13	0.72	112	196	106	99	0.65	0.71	0.97	0.94	0.89	1.30	1.06	1.27

3.4 | 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 4 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 4 (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

MORNINGSTAR CATEGORY	Apr-2018						3-year change		5-year change		10-year change	
	MFR (AVG)	MSR (AVG)	TYPE (AVG)	MFR (CUR)	MSR (CUR)	PC	MFR (CUR)	MSR (CUR)	MFR (CUR)	MSR (CUR)	MFR (CUR)	MSR (CUR)
EMERGING MARKETS	51	44	A	39	48	-	6	-7	4	1	2	2
FOREIGN LCG	46	44	A	30	52	-	20	-27	-1	-3	-27	27
FOREIGN LCV	44	39	A	15	72	-	4	-3	-26	27	-42	44
FOREIGN S/M C	11	74	A	13	65	-	-5	11	3	5	-21	33
FOREIGN S/M G	15	75	A	13	70	-	3	-6	2	-6	-18	36
FOREIGN S/M V	19	57	A	50	30	N	25	-20	12	-3	17	-10
LARGE CAP GROWTH	53	39	A	81	13	P	4	-3	-3	4	44	-42
MID CAP GROWTH	56	36	A	53	34	-	-19	16	-8	8	7	-8
SMALL CAP CORE	35	52	A	54	35	-	23	-21	16	-15	17	-14
SMALL CAP GROWTH	28	64	A	33	55	-	-15	15	-12	13	-6	6
SMALL CAP VALUE	39	45	A	58	26	N	26	-25	29	-28	26	-24
REAL ESTATE	39	43	A	38	44	-	-15	17	-21	26	-1	1
EM BOND	62	28	N	50	29	-	-17	15	-27	22	23	-16
FOREIGN LCC	56	32	N	34	55	A	16	-15	-13	13	-36	36
HIGH YIELD	63	31	N	52	36	A	-10	13	-10	11	-14	14
MID CAP CORE	65	25	N	65	21	-	-6	4	-8	8	-3	5
BANK LOAN	68	16	P	61	23	N	-9	13	10	2	-6	11
TIPS	74	17	P	67	9	-	-4	-1	22	-25	-5	1
INTER. TERM BOND	63	29	P	37	53	A	17	-18	25	-28	-40	38
MUNI NAT'L INT.	88	9	P	62	22	N	2	1	24	-20	-30	19
MUNI NAT'L L	84	7	P	60	17	N	1	-5	36	-35	-31	16
MUNI NAT'L S	84	9	P	62	17	N	-5	5	18	-13	-11	2
LARGE CAP CORE	72	20	P	77	15	-	1	-2	0	0	18	-17
LARGE CAP VALUE	69	26	P	53	37	A	-18	16	-12	13	-10	9
MID CAP VALUE	67	24	P	59	27	N	-24	19	-29	24	-12	10
COMMODITIES	77	11	P	43	29	N	-44	25	-35	24	--	--

KEY: **MFR** = Manager Fail Rate **MSR** = Manager Success Rate **PC** = Potential Changes

Table 4

Description of time trends (last 3, 5, and 10 years) in changes of the "Manager success rate" and "Manager failure rate" in various peergroups. "AVG" or "average" refers to the "whole sample results" discussed in Section 3 (see Table 2), and "CUR" or "current" refers the results from the most recent period in our rolling period trend analysis.

in the positive/negative alpha manager proportions through time. For example, to calculate the proportion of positive alpha managers ten years ago in, say, the large cap growth category, we would take the current value for this category (13) and subtract the 10-year change in the positive alpha managers (-42), giving us the proportion of 55. Thus, the Foreign LCG category has experienced significant decrease in the positive alpha manager proportion (55 to the current 13 percent) over the last ten years. Logically, the proportion of negative alpha managers for this category has experienced similar-size increase (44 percent), which means that ten years ago the negative alpha manager proportion in large cap growth was about 37 percent (81 - 44).

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 4, 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 several categories. For example, as illustrated in Figure 1[3], the intermediate term bond and high yield bond categories have experienced increases in the proportion of positive alpha managers (we will discuss the likely reasons for this shortly), whereas the large core category has steadily decreased its proportion of active managers for almost two decades, with the latest proportion of positive alpha active managers equal to just 15%.

In analyzing the last six columns of Table 4, which summarize the trends over the last three-, five-, and ten-year intervals for all the categories in our study, we notice several common denominators. First, the domestic large cap core, large growth, mid cap core, and mid cap growth categories have been on a gradual long-term trend of a decreasing proportion of positive alpha managers. This is due to the increasing competitiveness of these categories, as they attract both the most assets and the most number of managers.

Second, domestic fixed income categories have experienced a significant increase in positive alpha managers over the last decade—roughly since the recession of 2008. This effect is most likely because of the mismatch between the holdings of the most fixed income managers and the benchmark on one hand and the performance of the benchmark on the other. In particular, a recent paper by AQR concluded that "a significant portion of fixed income manager active returns comes from being overweight, structurally and permanently, sources of return that are highly correlated with high yield credit."[4] Figure 1 illustrates how the proportion of positive and negative alpha managers can change drastically over time, and that these changes appear to relate to the performance of these managers' benchmarks. For example, when the fixed income (and especially fixed income credit) asset prices collapsed at the beginning of the 2008 Financial Crisis, the proportion of positive alpha managers shrank drastically, since their portfolios (which were overweight credit securities), underperformed the benchmarks. The reverse happened once the Federal Reserve stepped in with its aggressive Quantitative Easing (QE) programs, resulting in a markedly increased proportion of positive alpha fixed income managers. As the effects of QE began to wear off (the last round of QE was announced in September of 2012), the proportion of positive alpha managers again started to shrink (see Figure 1).

Third, immediately following the 2008 Financial Crisis, the domestic value categories (large cap value, mid cap value, and small cap value) experienced a large increase in the proportion of positive alpha managers, but that proportion decreased precipitously over the next couple of years. Fourth,

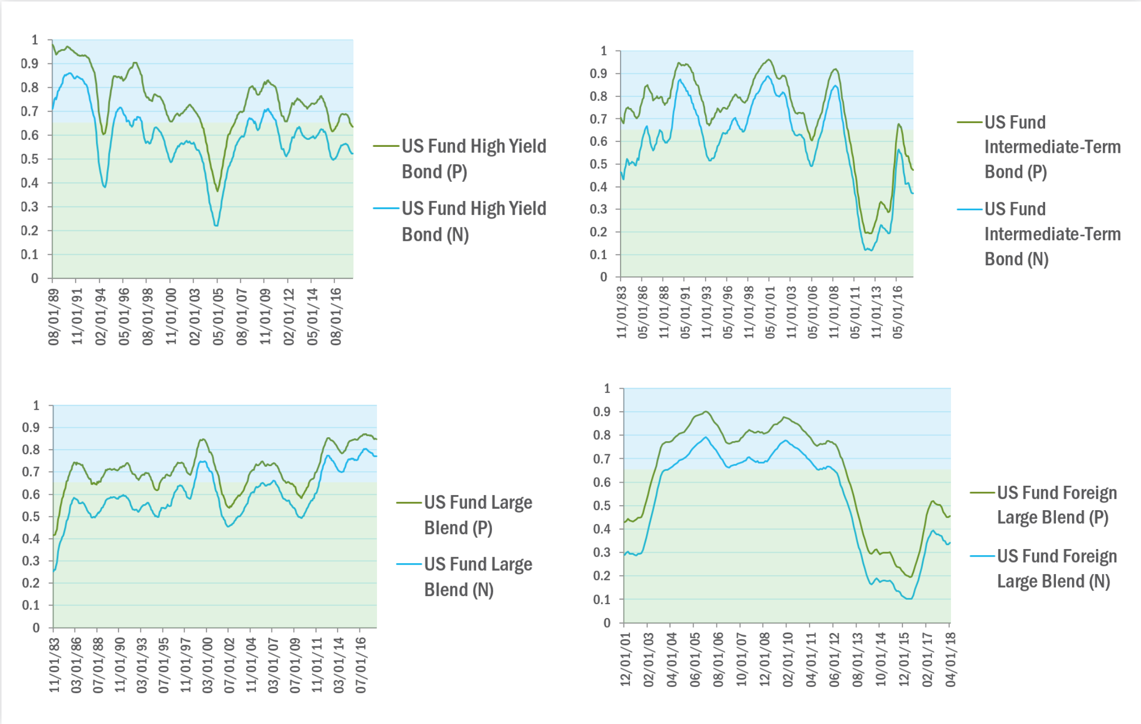

Figure 1

Time-trend of the percentiles of positive and negative alpha managers and their underlying benchmarks.

"N"/"P" refer to the proportion of negative/positive alpha managers, respectively. Note that the proportion of negative alpha managers will be equal to the distance between the "N" line and zero, while the proportion of the positive alpha managers will be equal to the distance between the "P" line and 1.

If the blue line N falls into the blue shaded area, it would be classified as Passive. If the green line P falls into the green shaded area, it would be classified as Active. If neither criteria are met, then it would be classified as Neutral.

all foreign large categories experienced a significant increase in the proportion of positive active managers after the 2008 Financial Crisis, and that proportion has decreased somewhat in recent years (see appendix).

3.5 | Machine Learning and Predicting Future Performance

In this section we discuss the results of applying machine-learning techniques to understanding the most relevant factors that have prediction power for the future net risk-adjusted return for active managers. We have carried out this analysis for a select set of categories – those that contain a large number of managers.

In particular, Figure 2 contains the results for the Large Blend category. The vertical panels correspond to various forecasting factors, such as historical risk-adjust return (CAPMalpha_lag), expense ratio (expRatio), manager tenure (managerTenure), fund size (fundSize), OLS regression slope (CAPMbeta),[5] tracking error against the benchmark, CAPMR2 (the OLS regression R2), fund turnover (turnover), and benchmark performance (benchmarkRet).

The horizontal axes of the panels denote units of the factors (for example, the expense ratio panel's x-axis goes from 0 to 2 percent). The vertical axis refers to the units of the forecasted variable: the future risk-adjusted return. The panels then represent the most appropriate relationship, as deemed by the machine-learning algorithm, between the forecasting factors and the future risk-adjusted return. The mean tendency of this relationship is represented by the blue line, while the red lines define the "confidence interval" of this relationship – the alternative values for the relationship between the forecasting factors and the future risk-adjusted return.[6]

The most important predictors of future alpha values are past performance, expense ratios and benchmark performance. All three of the results are intuitive: past performance is positively related to future performance; expense ratios, are negatively related to future performance; and benchmark performance is negatively related to future performance. Thus, the takeaway lesson from the machine-learning-driven algorithm comes down to common sense rules: managers with positive alphas tend to have done well in the past, have low expense ratios, and happen to have benchmarks that are underperforming.

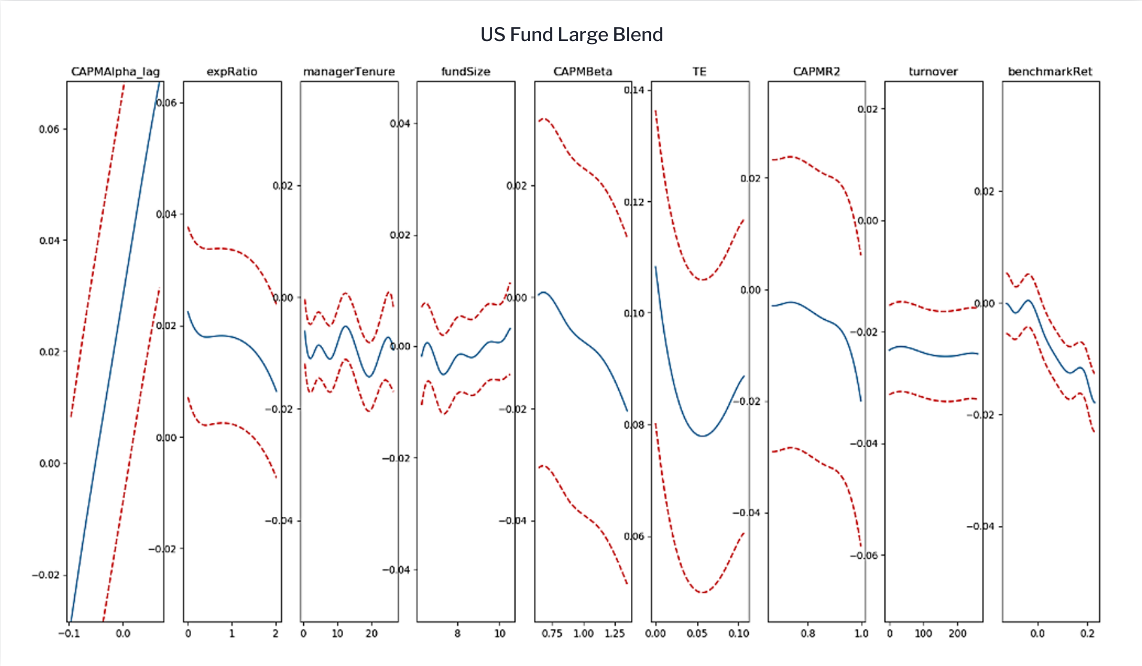

Figure 2

Description of the effect of various predictors (past alpha, expense ratio, manager tenure, fund size, beta, tracking error, R2, turnover, and benchmark performance) on future manager alpha.

Blue Line:

Depicts the mean relationship between the predictor and the future alpha.

Red Lines:

Give the confidence interval for the relationship

4 | SUMMARY

This version of the Active vs. Passive whitepaper, updating the previous results and introducing two additional strands of research, results in three 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.
- Finally, we used machine-learning techniques to confirm commonly held beliefs that past performance is positively related to future performance, whereas high expense ratios and performance in line with benchmarks may signal less-than-stellar future performance. Thus, investors and advisors should focus on these two dimensions when selecting a manager who would be more likely to generate positive alpha future performance.

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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Berk, Jonathan B. "Five Myths of Active Portfolio Management." Journal of Portfolio Management. 2005, Vol. 31, Issue 3, Pages 27-31.

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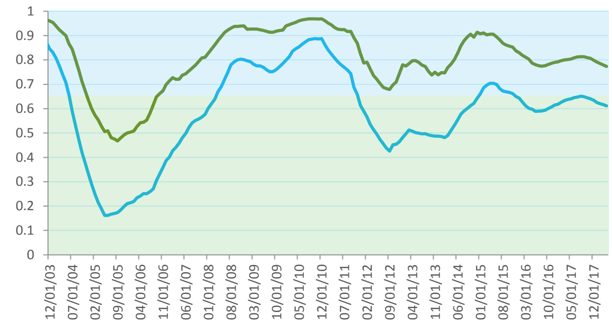
5 | APPENDIX

Appendix:

The proportions of Negative (blue line) and Positive (green line) alpha managers and their changes over time. The proportion of negative alpha managers will be equal to the distance between the "N" line and zero, while the proportion of the positive alpha managers will be equal to the distance between the "P" line and 1.

If the blue line falls into the blue shaded area, it would be classified as Passive. If the green line falls into the green shaded area, it would be classified as Active. If neither criteria are met, then it would be classified as Neutral.

*Note the begin dates are different across asset classes due to availability of data.



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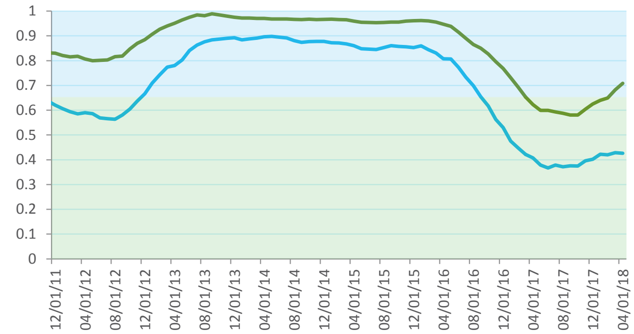

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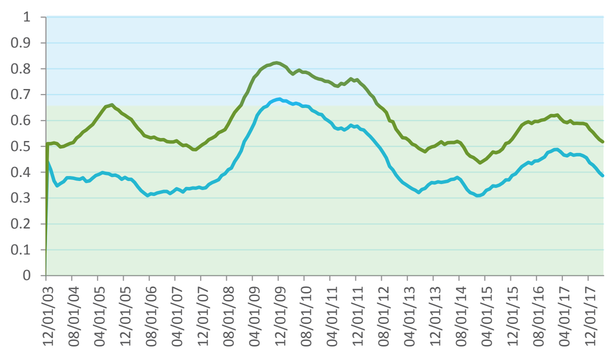

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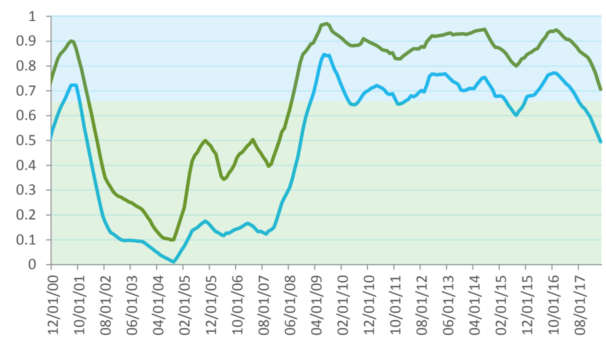

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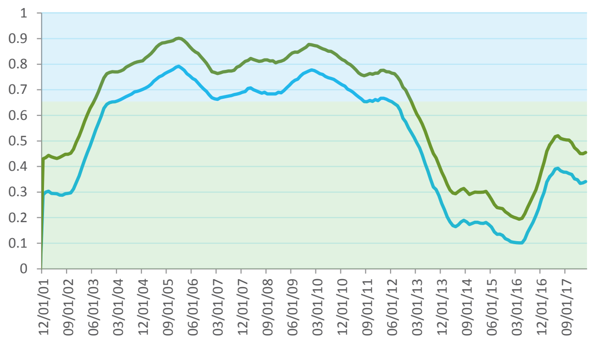

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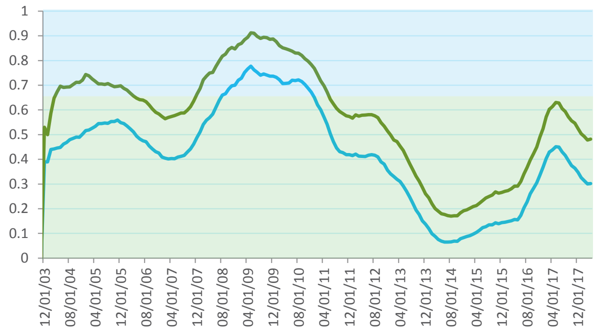

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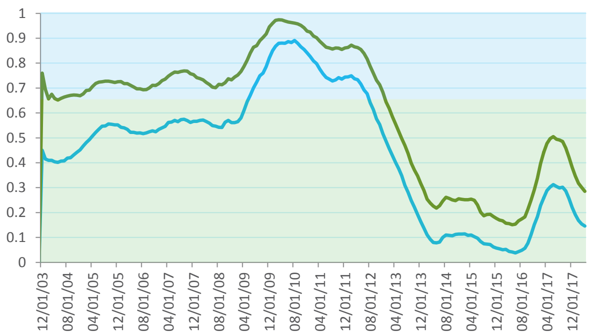

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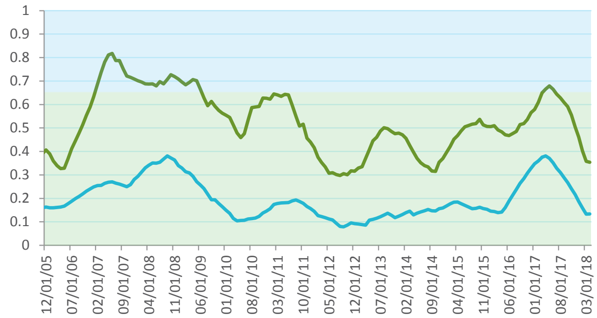

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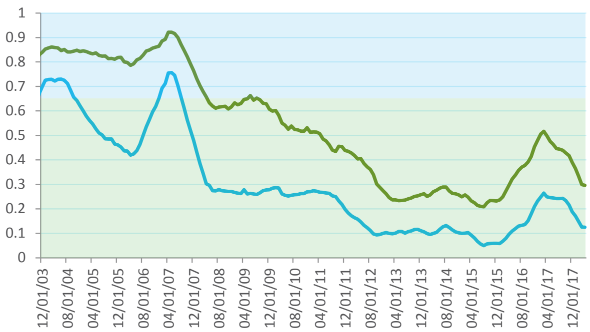

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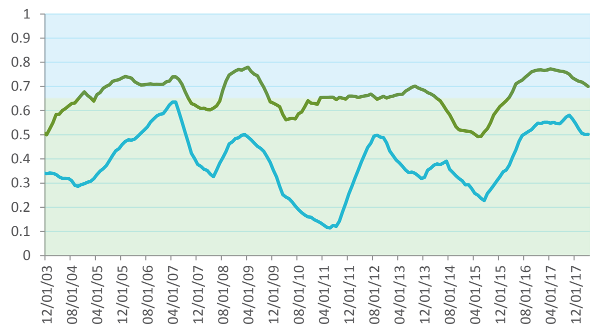

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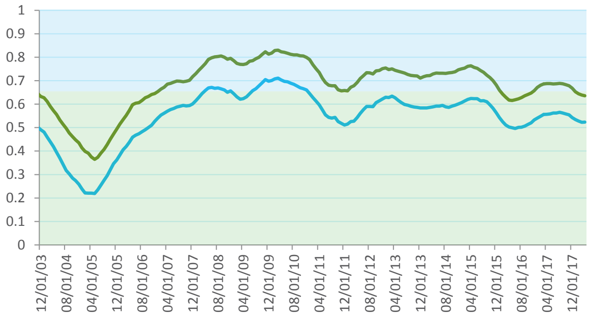

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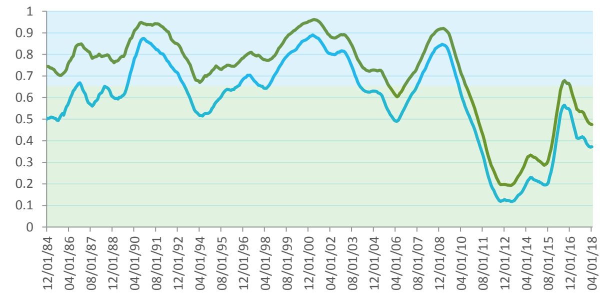

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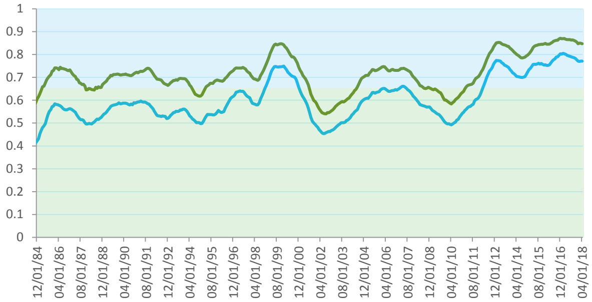

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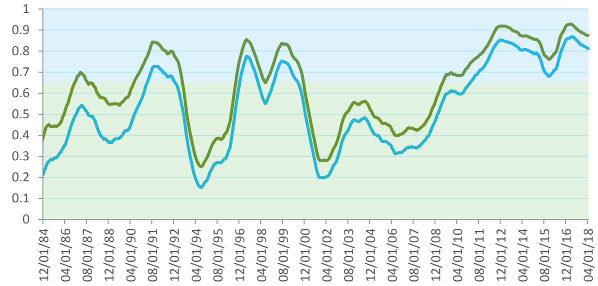

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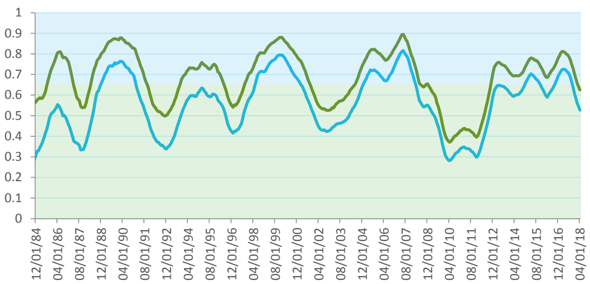

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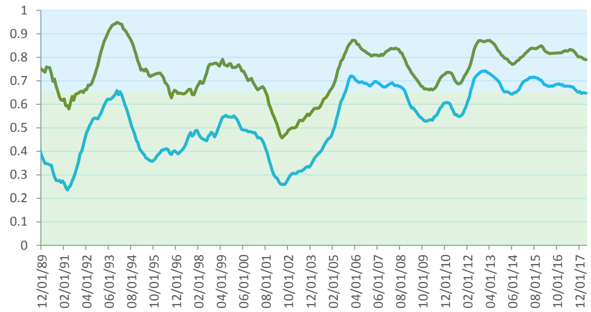

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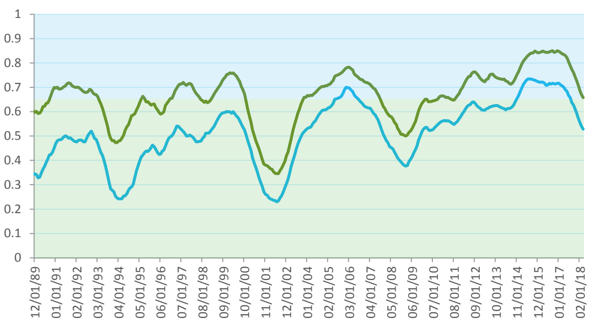

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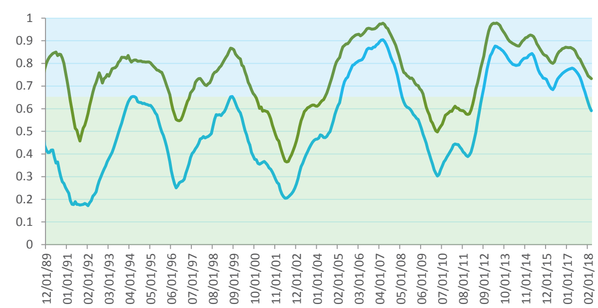

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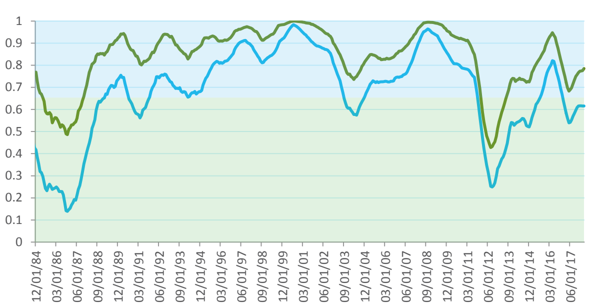

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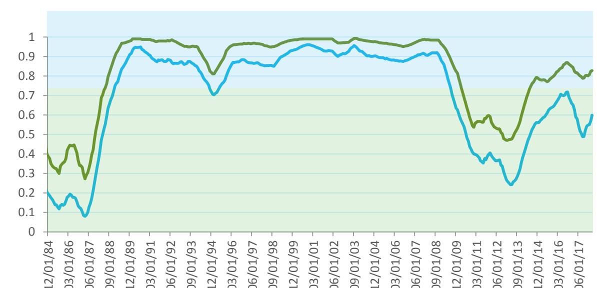

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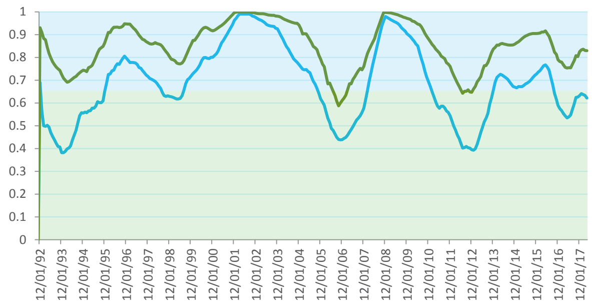

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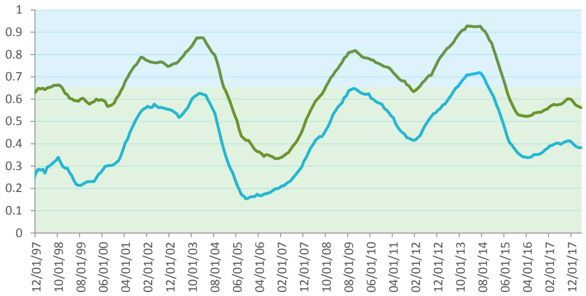

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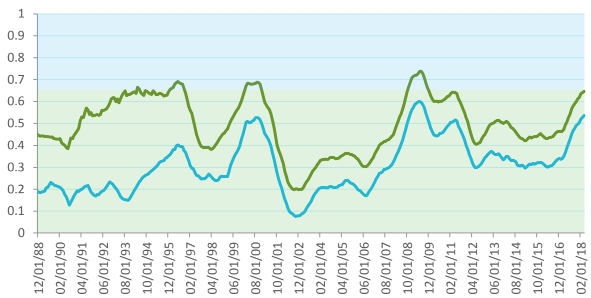

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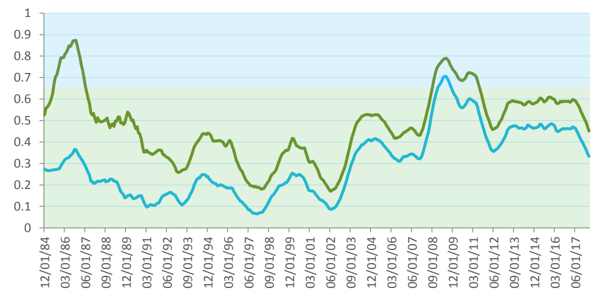

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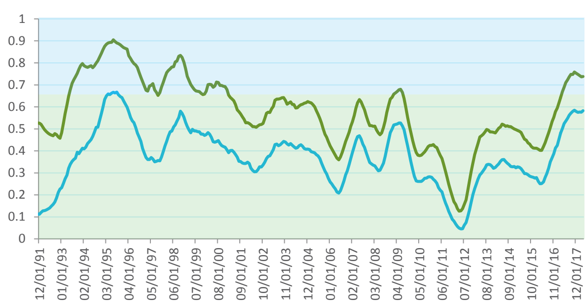

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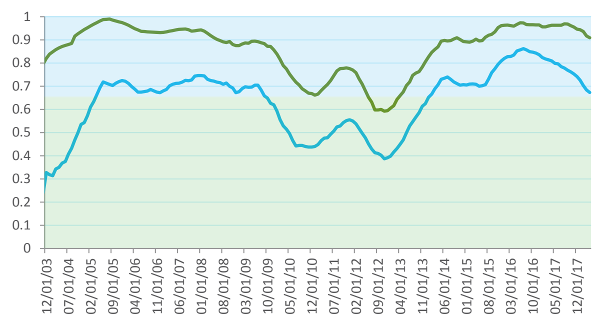

TIPS

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