Alpha Availability

Identifying the Drivers of Active Manager Returns Across Markets and Investment Styles

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Authors

Thomas Quinn, CFA
Managing Director
Senior Portfolio Manager, Tactical and Multi-Manager Strategies

Bin Cheng, CFA
Quantitative Research Analyst

Over the past decade, our research has taken multiple in-depth looks at the exogenous drivers of what we think of as "alpha availability" among active managers. Our original work focused on smaller AUM managers' ability to deliver relatively higher levels of alpha in various market environments ("*Survival of the Nimble*"). In early 2013 we expanded our analysis to identify active manager alpha drivers across markets and through time ("*Is Active Equity Management Alpha on Permanent or Temporary Disability*"). Building on our prior work, this study looks more in-depth at the concept of alpha availability (**Part 1**). We analyze the drivers of alpha availability with advanced techniques and higher resolution data (**Part 2**). Finally, we take a top-down look at the differences in quantitative managers' return pattern vs. their fundamental peers (**Part 3**), which our colleagues wrote about earlier this year ("*A Challenging Environment for Quant Strategies*").

Key Takeaways from This Analysis:

- High Active share is a necessary, but not sufficient condition for high levels of excess return. Active share magnifies the skill (or lack thereof) of the manager. The availability of alpha due to market conditions will have the largest impact on highly active managers.
- The ideal market for active managers isn't simply a bear market. In developed markets, active strategies perform best when there is concentrated weakness in benchmarks (a heavily weighted concentration in stocks lagging the index). This is almost always true in bear markets, but it is also common in the early cycle market rebounds.
- Periods of large, concentrated benchmark weakness are infrequent and difficult to predict. More actionable factors that coincide with high levels of alpha availability are a low to moderate liquidity environment, moderate levels of factor skew, low correlations amongst stocks and well-defined expectations for economic policy.
- The drivers of alpha availability are unique to the markets they operate in as well as the investment approach. There are distinct factors which benefit quantitative managers over fundamental managers and vice versa.

Note to reader: Our use of the term "manager" represents the collective investment decision-making mechanisms of an investment strategy or portfolio. It includes the investment staff, systems, and quantitative models employed.

Alpha Availability

Identifying the Drivers of Active Manager Returns Across Markets and Investment Styles

Part 2

Quantifying Alpha Availability

In **Part 1** of this study we provide evidence supporting the validity of alpha availability; the idea that the macro environment and market dynamics will impact active managers' ability to beat their benchmark and style. Now, we use the median manager's performance within a universe as a proxy for alpha availability to identify those explanatory factors. We chose all actively managed SMA products with at least 3 years of history in 3 broad categories. U.S. Large Cap, Non-U.S. Large Cap, and Emerging Markets. For every 12 months, ending 12/31/1998 through 12/31/2020, we calculate the products' gross excess return vs. the best-fitting benchmark.[1] This last step is extremely important and a noticeable improvement upon prior work we have done. Matching each strategy to the most appropriate benchmark (Value, Growth, or Core) provided 2 distinct benefits; we significantly broaden our universe by including dedicated value and growth products and we remove the style bias from managers that have incorrectly classified themselves in the database (which is very common in the non-U.S. and EM universes).

Our analysis's Independent variable is the Universe median of 12 month trailing excess returns for each month in the sample.

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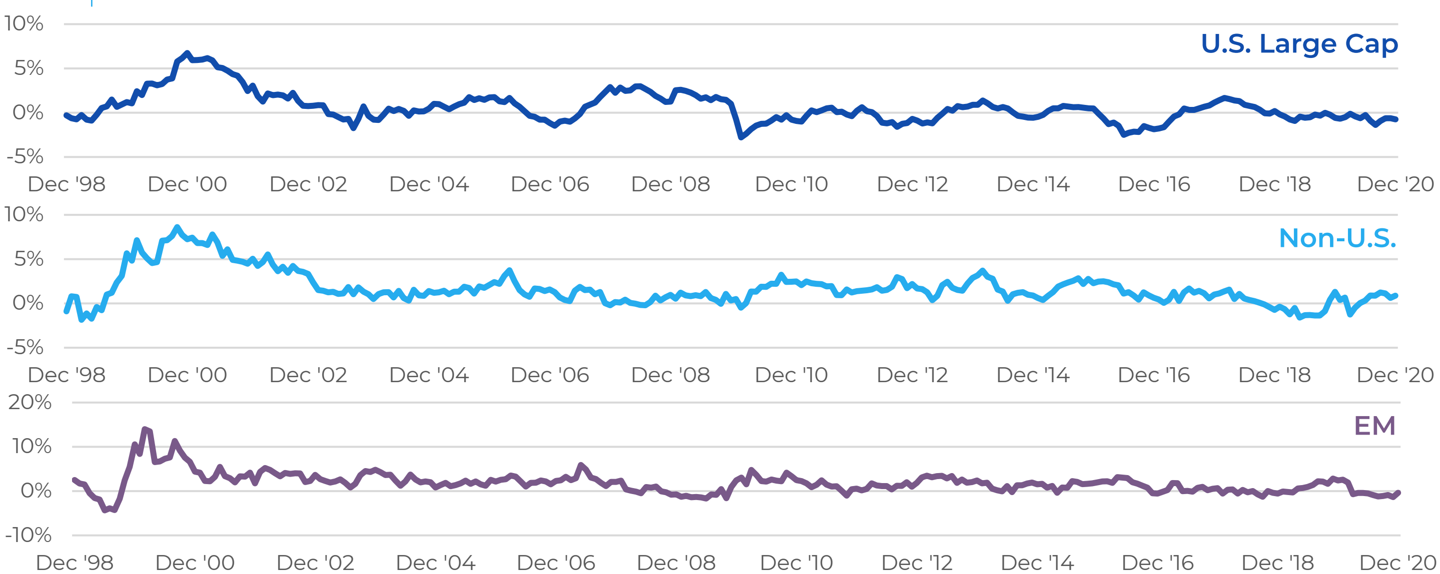
Chart 4 Median 12m Excess Return



Source: Evestment Monthly Database, MPI Stylus, Xponance Investment Research.

[1] Best fit benchmarks were selected for each product from the following list based on maximum R-Squared to the product: U.S. LC: S&P 500 (Core, Value, Growth), Russell 1000 (Core, Value, Growth), Russell 2500 (Core, Value Growth). Non-U.S.: MSCI EAFE (Core, Value, Growth), MSCI ACWIxUS (Core, Value, Growth). EM (MSCI EM (Core, Value, Growth). All indices are Net Returns in U.S. Dollars. R-Squared is calculated for the entire common history of the product and benchmarks using monthly data.

Table 1

	Minimum Products	Maximum Products	Average 12m Excess	Median 12m Excess	% Positive 12m Periods
U.S. Large Cap	617	1277	0.60%	0.43%	58.5%
Non-U.S.	182	584	2.11%	1.32%	89.8%
Emerging Markets	60	306	2.23%	1.83%	80.4%

Source: Evestment Monthly Database, MPI stylus, Xponance
All Separate Account Strategies with 36 months of reported gross returns between 1/1998-12/2020. Universes: (EM = All Emerging Market Equity, U.S. LC = All U.S. Large Cap Equity, Non-U.S. = All EAFE Equity and All ACWI ex-U.S. Equity)

The strong performance of the median manager may come as a shock. That does not track the experience of most allocators over the past 20+ years (ourselves included). We believe this is due to the following biases in the data:

- Gross vs. net returns – All else being equal, 50% of managers beating the benchmark PRIOR to fees is a reasonable premise.
- Self-Reporting (Selection bias) – The Evestment database includes products no longer reporting returns, which prevents the most problematic survivorship bias elements. However, the fact that the database is self-reported will skew the data upward. Some firms are selective with the choice of strategies they report on. It is common to see only products with successful track records included. When added, their history is backfilled for the strategy's life, biasing the peer groups upward.
- Combining Model / Paper returns with live returns. You can exclude model and paper portfolio returns, this classification is based on self-reported data, which can be inconsistently reported.

To ensure that the biases in the data did not skew our results, we ran the same analysis on various mutual fund universes. The magnitude of excess returns is higher in our sample, but the returns were highly correlated regardless of source, allowing us to continue testing.

Selecting Explanatory Variables

The variables selected leveraged our decades of experience allocating to active managers, with many being modifications of the variables included in our 2013 paper.[2] The factors reflect many of the narratives active managers and allocators cite when explaining returns. The macro-environment is not heavily represented in our variable set, including only Liquidity and Policy Uncertainty. We believe that other macro variables express themselves more clearly through the market dynamic variables included in the study.

The improved design of our concentrated gain and loss variables seen below was the most considerable step forward in model efficacy. Recent experience suggested that concentrated skew within benchmarks was having an outsized impact on active managers' success. The issue commonly cited by managers was the combination of index concentration and performance, rather than just stock level dispersion. Outsized contribution to benchmark return is what mattered. Also, we separated positive and negative benchmark contributions into two distinct factors.

These variables ended up being so powerful that many factors used in prior analysis were no longer viable and excluded from the models.

Independent Variables

Policy Uncertainty – Economic Policy Uncertainty Indicator

This variable is based on the Economic Policy Uncertainty Index®, which is designed to measure policy-related economic uncertainty. It constructs a normalized index of the volume of local news articles discussing economic policy uncertainty. For regional indices, it takes a GDP weighted average approach to calculate the composite readings. We took a trailing 12-month average to uncover the underlying trends of this variable. This factor captures the macro backdrop that we believe has a significant impact on active managers' relative performance.

Concentrated Losses – Bottom Ten Largest Negative Contribution

This variable represents the largest ten negative performance contributions within the respective benchmark for each region. We have also adjusted it for the direction of the market, subtracting a hypothetical 10 stock contribution from an equally weighted index where all stock returns were equal to the benchmark (idealized "flat" market). We took a trailing 12-month average to uncover the underlying trends of this variable. When large index constituents underperform the index, active strategies who often have lower weights to the largest constituents stand to benefit.

Concentrated Gains – Top Ten Largest Positive Contribution

This variable represents the opposite side of the factor listed above. It measures the largest ten positive contributions within the respective benchmark for each region. We have also adjusted it for the direction of the market, using the same approach as the Concentrated Loss variable. We took a trailing 12-month average to uncover the underlying trends of this variable.

[2] The 2013 paper, found as measured by stock return dispersion, stock correlations, Index of Economic Policy Uncertainty, Magnitude of Fed policy (as proxied by the Liquidity indicator) and the return dispersion between small and large cap stocks. to be the most significant drivers alpha availability for U.S. Large Core Managers.

Correlation – Pairwise Stock Correlation

This variable measures the average correlation among stocks within the relevant benchmark. In our prior 2013 study, stock correlation was a significant negative factor in explaining active managers' relative performance. We believe this factor's assumption still holds true; elevated correlations negatively impact the alpha of active managers because fundamental factors, which most active managers evaluate to generate alpha, are overwhelmed by generalized movements in the market. We took a trailing 12-month average to uncover the underlying trends of this variable.

Liquidity – Xponance Liquidity Regime Indicator

This variable is designed to measure the global business cycle liquidity by three different components: central bank rates action, sovereign spread, and currency volatility from major G20 countries. It is calculated as a diffusion index and is a proxy for global credit loosening/ tightening. Our assumption is when liquidity is injected into markets and remains at elevated levels, it lifts all boats. High liquidity is a headwind for active managers, who utilize fundamental factors to select stocks. We expect fundamentals to show less efficacy when all risk is being rewarded.

Style Skew – Absolute Value of (12 month Value – Growth performance)

This variable measures the absolute dispersion of style performance. The leaderships in markets are often led by a group of stocks that share similar characteristics, for example, the recent years of growth outperformance. When a single investment style dominates a market, the majority of active managers with multi-dimensional approaches will face headwinds relative to the benchmark. We took a trailing 12-month average to uncover the underlying trends of this variable.

Size Skew – Absolute Value of (12 month Cap Weighted – Equal Weighted Index performance)

This variable measures the absolute dispersion of size performance. It echoes the market experience of the style skew variable in that when size is the dominant driver of market returns, the majority of active managers that avoid extremely skewed market cap tilts, will face performance challenges. Similar to the observation from style dispersion variable, the absolute level of dispersion, regardless of which side leads, matters the most. We took a trailing 12-month average to uncover the underlying trends of this variable.

Sector Skew – Absolute Value of (12 month Economically Sensitive – Defensive Sector[3] performance)

This variable represents the absolute dispersion from a sector perspective. A persistent market trend could also be led by a specific cluster of sectors, similar to the other skew related variables, we expect the majority of diversified active managers to face performance pressure during periods of high skew. We took a trailing 12-month average to uncover the underlying trends of this variable.

[3] We conducted a K-Means clustering analysis on all sector returns (U.S., EAFE and EM) and identified two significant sector clusters. We intuitively refer to the clusters as Economically Sensitive (Consumer Discretionary, Industrials and Information Technology) and Defensive (Consumer Staple, Communication Services, Health Care and Utilities).

Methodology

The analytical task is to identify significant drivers and regimes that could explain alpha availability (as defined above) across markets and through time. Linear regression is imperfect for time series analysis with overlapping periods as discussed in our prior study. We chose a machine learning, regression tree methodology which can capture nonlinear relationships and distinguish the relative importance of variables. We were mindful of avoiding over complexity/ fitting and ambiguous interpretation of the model outcomes that some of the advanced methodologies could lead to. The regression tree methodology balances our need for analytic enhancements while avoiding the pitfalls common with other machine learning approaches.

A regression tree is a supervised algorithm used in machine learning. The data is recursively split into two groups based upon a simple threshold value for a variable. The tree's final branches represent the predicted values of the model, in this case the excess return of the median active manager in each universe. The algorithm will choose each branching of the data (variable and threshold level) based upon a cost function, where the cost is the loss of accuracy. The algorithm's cost function and recursive nature will order the variables by predictive impact, with the most important variables being higher in the tree. To find the predicted value associated with this model, we simply follow the tree-based logic using the observation's characteristics. The process works exactly like a standard decision tree with a series of Yes or No questions. The advantages of this methodology to our study:

a) It accommodates nonlinear relationships. The regression tree methodology does not expect the data to be linear.

b) It provides the relative importance of variables as a straightforward output. The output gives us a clear understanding of the model drivers in ranked order.

c) The outcomes can be interpreted in a clean and straightforward format. It helps to understand the model and identify the underlying story behind the data.

d) It avoids unnecessary complexity and overfitting. The issue of over complexity/ fitting could bring up false relationships and ambiguous interpretation of the model outcomes, especially with highly correlated independent variables and overlapping time series.

Analysis 1

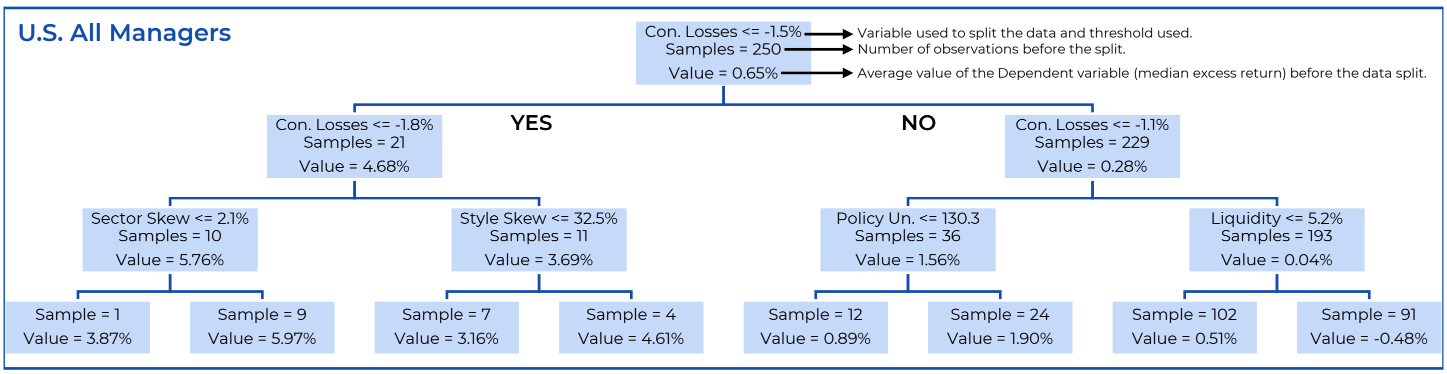
All Active Managers – Concentrated Gains and Losses

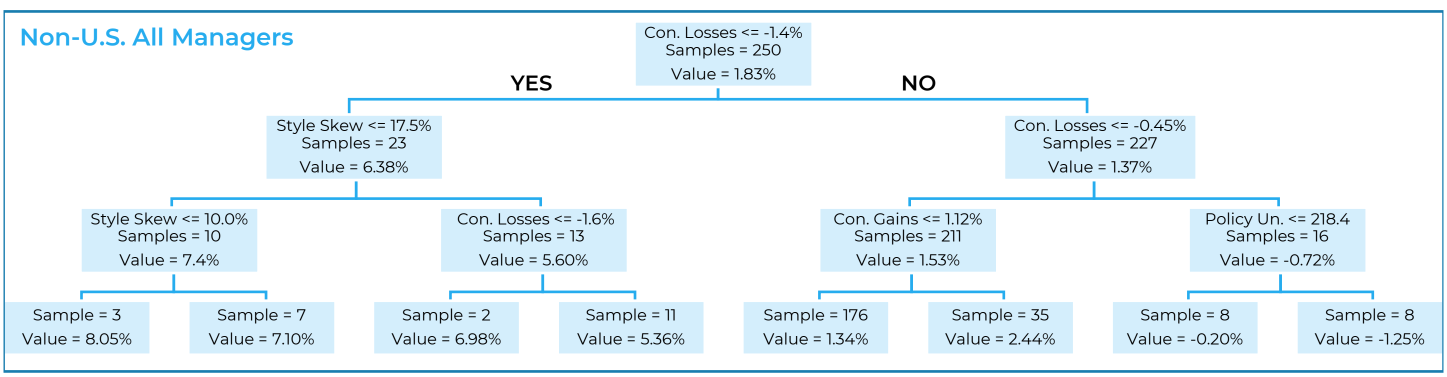
Our first analysis tested our variables against the alpha availability of 3 broad regional peer groups. The results look promising, with R-squared values ranging from 68 – 75% and the directional relationships matching our intuition.

Table 2 | **Feature Importance (% contribution to R-Squared)**

	U.S. Large Cap	Non-U.S.	Emerging Markets
Concentrated Gains	--	5.3%	73.3%
Concentrated Losses	87.9%	91.0%	
Policy Uncertainty	1.5%	0.7%	5.7%
Style Skew	1.0%	--	5.7%
Size Skew	--	--	--
Sector Skew	0.8%	3.0%	
Correlation	--	--	18.6%
Liquidity	8.8%	--	--
R-Squared	71.1%	74.6%	67.9%

Green indicates a positive relationship with Alpha availability. Red indicates a negative relationship.





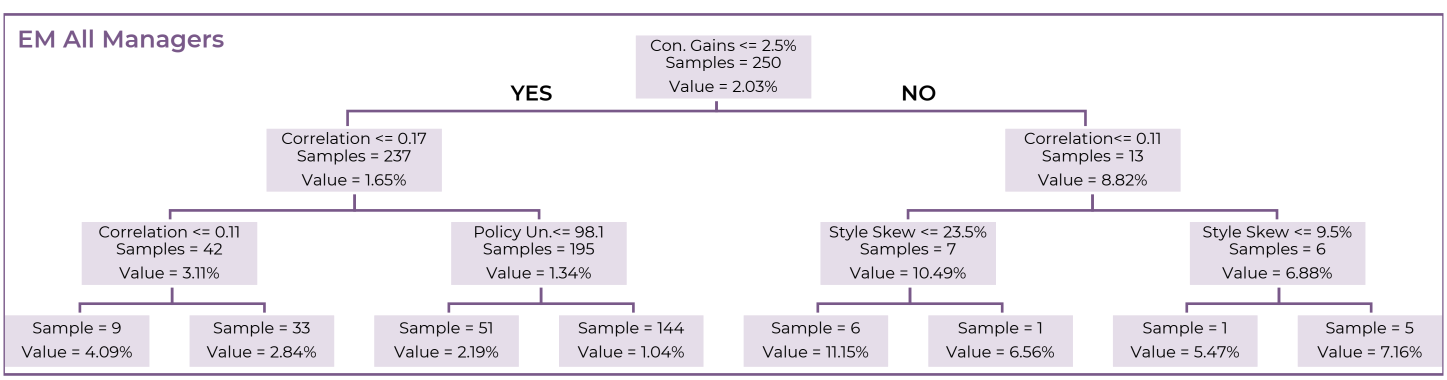
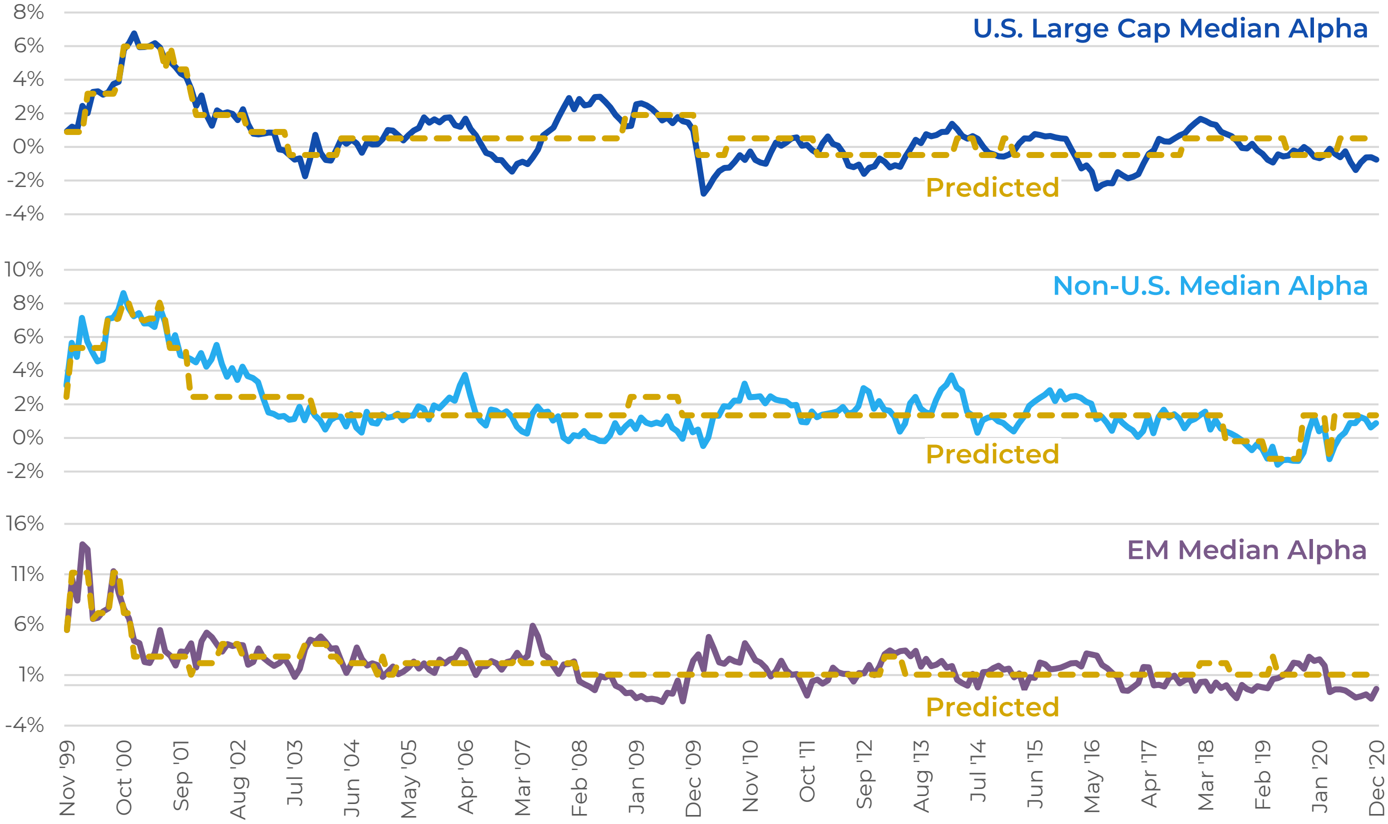


Chart 5 | **Prediction vs Actual: Alpha Availability Model**



Source: Xponance Investment Research, Python (DecisionTreeRegressor package).

Table 3 | **Interpretation of Results**

U.S. Large Cap Active Managers

Variable	Directional Impact	Interaction (Path dependencies)	Critical Values	Results
Concentrated Losses	The variable always had a positive relationship with alpha availability. When large concentrated loss happened in the benchmark, active managers tended to deliver greater alpha (alpha availability was high).	This factor was used in all observations dominated the explanation of variation. It accounts for 88% of the contribution to R2.	-1.12% is the minimum threshold to differentiate large concentrated losses.	High concentrated losses regime: 57 observations, average median excess return = 3.1%. Normal concentrated losses regime: 193 observations, average median excess return = 0.04%
Liquidity	When used, the variable had an inverse relationship with alpha availability. Periods of high liquidity coincided with periods when active managers produced less alpha.	This factor was used in 193 observations, when Concentrated Losses were not high, accounting for 8.8% of the contribution to R2.	0.05 is the threshold selected by the model to differentiate high from low liquidity regimes.	High liquidity regime: 91 observations, average median excess return = -0.48%. Low liquidity regime: 102 observations, average median excess return = 0.51%.

Table 3 Cont'd

Non-U.S. Active Managers

Variable	Directional Impact	Interaction (Path dependencies)	Critical Values	Results
Concentrated Losses	The variable always had a positive relationship with alpha availability. When large concentrated loss happened in the benchmark, active managers tended to deliver greater alpha (alpha availability was high).	This factor was used in all observations dominated the explanation of variation. It accounts for 91% of the contribution to R2.	-1.4% is the minimum threshold to differentiate large concentrated losses and -0.45% is the maximum threshold to differentiate low concentrated losses.	High concentrated losses regime: 23 observations, average median excess return = 6.4%. Normal concentrated losses regime: 211 observations, average median excess return = 1.53% Low concentrated losses regime: 16 observations, average median excess return = 0.72%
Liquidity	When used, the variable had an inverse relationship with alpha availability. Periods of high liquidity coincided with periods when active managers produced less alpha.	This factor was used in 193 observations, when Concentrated Losses were not high, accounting for 8.8% of the contribution to R2.	0.05 is the threshold selected by the model to differentiate high from low liquidity regimes concentrated losses.	High liquidity regime: 91 observations, average median excess return = -0.48%. Low liquidity regime: 102 observations, average median excess return = 0.51%.

EM Active Managers

Variable	Directional Impact	Interaction (Path dependencies)	Critical Values	Results
Concentrated Gains	The variable always had a positive relationship with alpha availability. When large concentrated gains happened in the benchmark, active managers tended to deliver greater alpha (alpha availability was high).	This factor was used in all observations dominated the explanation of variation. It accounts for 73% of the contribution to R2.	2.45% is the threshold selected by the model to differentiate large concentrated gains.	High concentrated gain regime: 13 observations, average median excess return = 8.8%. Normal concentrated gain regime: 237 observations, average median excess return = 1.7%
Correlation	When used, the variable had an inverse relationship with alpha availability. Periods of high correlations between index constituents coincided with periods when active managers produced less alpha.	This factor was used in all observations, accounting for 19% of the contribution to R2.	0.17 is the threshold selected by the model to differentiate high vs. low correlation regimes under the condition of normal concentrated gains regime.	Low correlation regime: 42 observations, average median excess return = 3.1%. High correlation regime: 195 observations, average median excess return = 1.3%.

Concentrated Gains and Losses

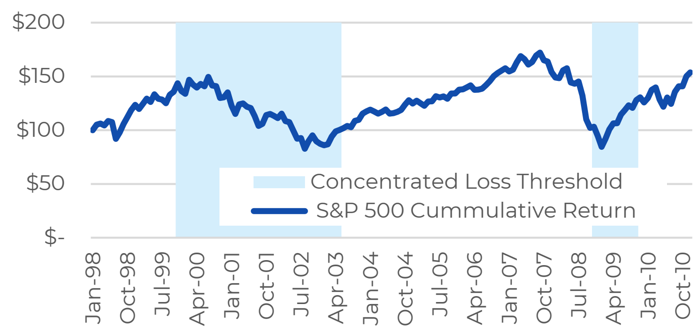
Our fully developed measures of concentrated gains and losses are potent variables. Collectively, they explain almost all the variation in the model predictions for U.S. and Non-U.S. universes, and almost 75% in the Emerging Market Universe.

The insights offered by a model-driven by concentrated index gains and losses are significant but hardly revelatory. The logic of this model is widely accepted by allocators. When heavily weighted index constituents dramatically underperform the broad market, not being invested in the largest index stocks is a huge structural performance advantage. The model for EM managers uses concentrated gains rather than losses as the lead variable. However, the 13 periods when concentrated gains were above the stated threshold, concentrated losses were also substantial. The model results would have been almost as strong, swapping those factors in the EM model. The 13 observations occurred early in our testing period. Emerging Market investing, and the equity markets themselves have changed dramatically in the past 20 years (Hong Kong listed Chinese shares were not added until 2000 and represented only 5.6% of the index). In Part 3 of our analysis, we show that Concentrated gains are the most significant headwind to active managers in the EM analysis if you only include 2003 onward.

There are some more subtle insights resulting from this initial analysis that we believe to be useful for allocators. There is a common belief that active managers earn their fees during bear markets (The relationship between bear markets and high alpha generation is strong). When you look through the lens of concentrated losses, you can see that the period after a sharp market loss is just as advantageous to active managers. Being heavily invested in high active share managers will pay dividends during the start of a bear market. If you miss that opportunity, these results suggest that the early stages of market recovery are equally as strong for highly active managers.

Chart 6 shows the periods when the S&P 500 experienced concentrated losses (and active managers thrived). While the 12m windows began during down markets, the environment persisted well into the market recovery. Both periods highlighted also represented substantial regime shifts, where long-standing market leaders were the source of market losses. **Table 4** (on the next page) shows the respective peaks in the concentrated loss variable during the Dotcom crash and Great Financial Crisis, as well as the heavily weighted stocks that contributed to the level of losses.

Chart 6 **Timing of Concentrated Losses in the S&P 500**



Source: Xponance investment research and Factset Research Systems.

Table 4 **Largest Negative Ten Contributors**

9/30/2000 Largest Negative Ten Contributors	
Intel Corporation	-1.62%
Cisco Systems, Inc.	-0.69%
Lucent Technologies Inc.	-0.28%
Microsoft Corporation	-0.27%
IBM	-0.25%
Texas Instruments Incorporated	-0.25%
Dell Inc.	-0.20%
Oracle Corporation	-0.19%
JDS Uniphase	-0.16%
Applied Materials, Inc.	-0.16%
S&P 500 Return	-4.69%
Total Contribution (10 Largest)	-4.07%
10 "Average" Stocks	-0.09%
Concentrated Loss	**-3.97%**

10/31/2008 Largest Negative Ten Contributors	
General Electric Company	-0.47%
Bank of America Corp	-0.46%
Citigroup Inc.	-0.35%
Schlumberger NV	-0.32%
ConocoPhillips	-0.31%
Microsoft Corporation	-0.30%
IBM	-0.27%
Cisco Systems, Inc.	-0.24%
PepsiCo, Inc.	-0.20%
Coca-Cola Company	-0.20%
S&P 500 Return	-17.46%
Total Contribution (10 Largest)	-3.12%
10 "Average" Stocks	-0.35%
Concentrated Loss	**-2.78%**

Source: Xponance investment research and Factset Research Systems.

Finding Actionable Insights

Across markets, high levels of concentrated gains and losses are rare and difficult to forecast. The goal of our work is always actionable insight. With that in mind, we executed a secondary analysis, isolating the periods that do not have a signal driven by concentrated gains and losses. The remaining periods experience relatively balanced index participation. **Chart 7** (on page 12) shows truncated regression trees, highlighting the periods we used in our additional analysis.

Analysis 2

Finding Actionable Insight

All Active Managers – "Balanced" markets only

As described above, the first branch of our initial regression tree resulted in isolating extreme values of concentrated gains and losses from the rest of the sample. These cutoffs were extremely valuable in the original model's efficacy but were not actionable from an allocator's perspective. This analysis removes the observations that saw their predicted value driven solely by the concentration variables' level **Chart 7** (on page 12). The description of each subset is detailed in **Table 5**.

Table 5

	All Periods Median Excess	% Positive 12m Periods	Analysis 2 Median Excess	Analysis 2 % Positive 12m Periods
U.S. Large Cap	0.43%	58.5%	0.04%	46.6%
Non-U.S.	1.32%	89.8%	1.50%	95.7%
Emerging Markets	1.83%	80.4%	1.65%	82.7%

See Table 1 for full data description. Updated data: U.S. Active Strategies: The samples that were excluded from this analysis had bottom 10 contributions more negative than -1.12% which were 11/30/1999 – 5/31/2003 and 11/30/2008 – 12/31/2009. Non-U.S. Active Strategies: The samples that were excluded from this analysis had bottom 10 contributions more negative than -1.395 and less negative than -0.445 which were 11/30/1999 –10/31/2001 and 7/31/2018 – 9/30/2019. Emerging Market Strategies: The samples that were excluded from this analysis had top 10 contributions larger than 2.45 which was 11/30/1999-11/30/2000.

Alpha Availability: Part 2

Chart 7 | **Identifying Periods with Balanced Index Participation**

All U.S. Active Strategies (12/98 – 12/20, monthly)
Trailing 12m excess return (Peer Median)
Observations: 250
Average Value: 0.65%

What was the level concentrated losses in the S&P 500?
Attribution of 10 largest negative contributors relative to the average stock in the index – trailing 12m

Very High (<-1.82%)
Obs: 21
Average: 4.68%

High (<-1.12%)
Obs: 36
Average: 1.56%

All Other Periods
Obs: 193
Average: 0.04%

All Non-U.S. Active Strategies (12/98 – 12/20, monthly)
Trailing 12m excess return (Peer Median)
Observations: 250
Average Value: 0.65%

What was the level concentrated losses in the MSCI EAFE Index?
Attribution of 10 largest negative contributors relative to the average stock in the index – trailing 12m

Very High (<-1.4%)
Obs: 23
Average: 6.38%

Moderate (between -0.45% & -1.4%)
Obs: 211
Average: 1.53%

Low (>-0.45%)
Obs: 16
Average: 0.72%

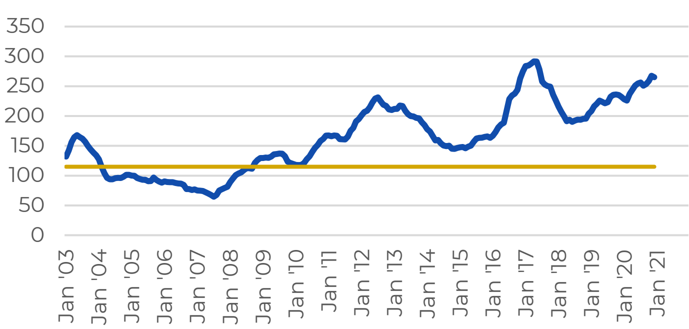
All EM Strategies (12/98 – 12/20, monthly)
Trailing 12m excess return (Peer Median)
Observations: 250
Average Value: 2.03%

What was the level concentrated losses in the MSCI EM Index?
Attribution of 10 largest negative contributors relative to the average stock in the index – trailing 12m

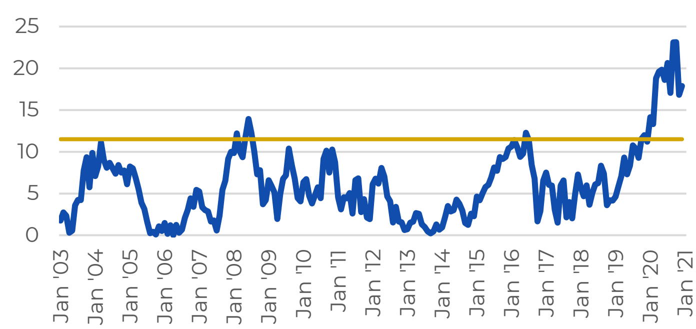
All Other Periods
Obs: 237
Average: 1.65%

Very High (>1.82%)
Obs: 13
Average: 8.82%

Chart 9 | **Policy Uncertainty**



Style Skew

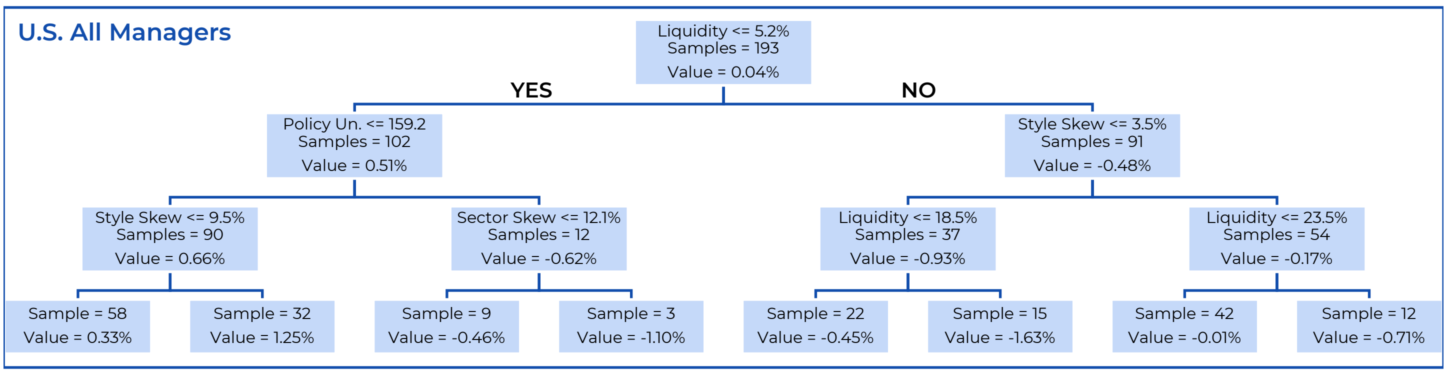


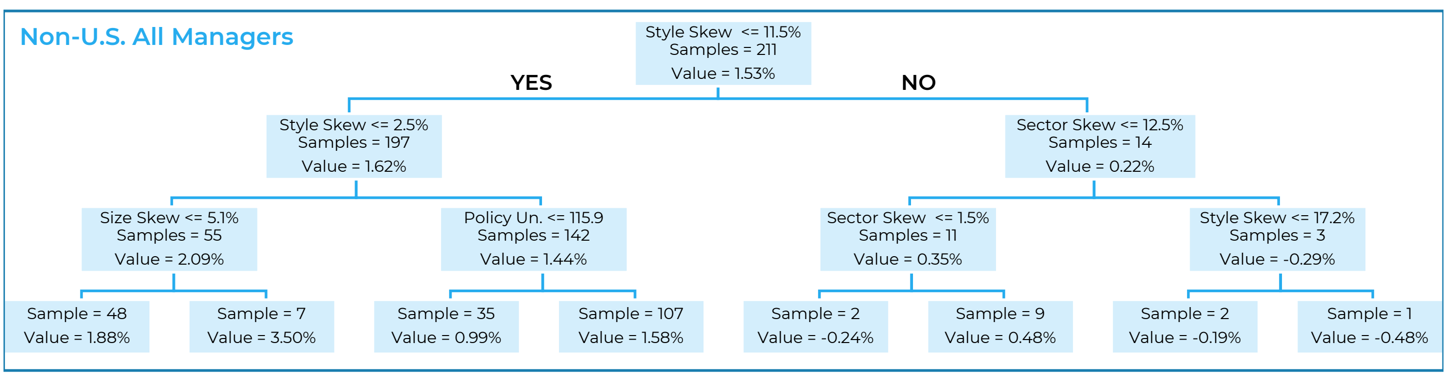
Variables & Analysis

We included all explanatory variables outside of concentrated gains and concentrated losses. The regression tree methodology was identical to Analysis 1. **Table 3** (on pages 8-9) are the results of the secondary analysis in isolation.

Table 6 | **Feature Importance (% contribution to R-Squared)**

	U.S. Large Cap	Non-U.S.	Emerging Markets
Policy Uncertainty	15.5%	13.1%	26.2%
Style Skew	27.0%	61.2%	--
Size Skew	--	23.0%	--
Sector Skew	0.8%	2.6%	--
Correlation	--	--	67.3%
Liquidity	56.7%	--	6.5%
R-Squared (original)	71%	75%	68%
R-Squared (Enhanced)	80%	78%	72%





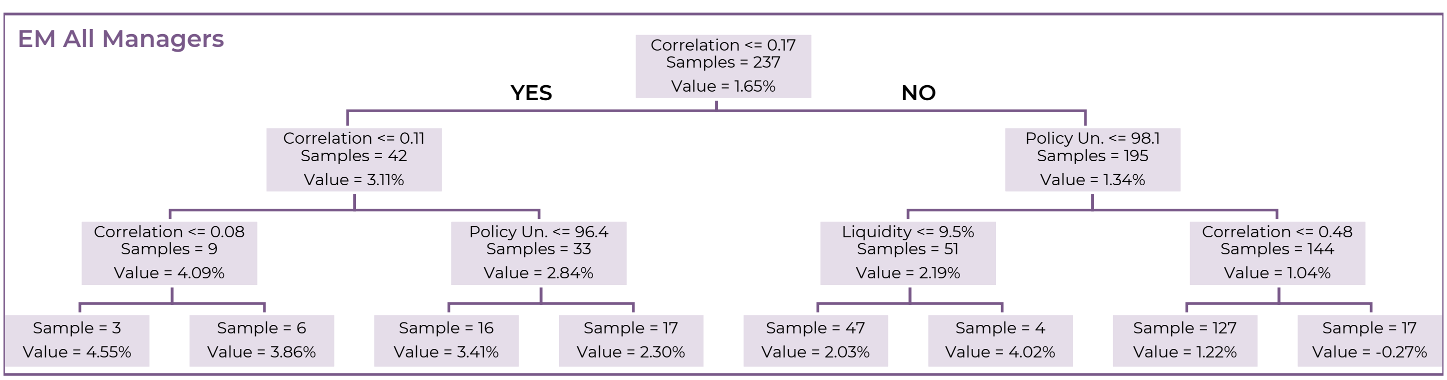


Table 7

U.S. Large Cap Active Managers

Variable	Directional Impact	Interaction (Path dependencies)	Critical Values	Results
Liquidity	Liquidity had an inverse relationship with alpha availability. Periods of high liquidity coincided with periods when active managers produced less alpha.	This is the most important factor that explains variation for secondary analysis. It accounts for 57% of the contribution to R2.	5% is the threshold to differentiate high vs. low liquidity regimes.	Low liquidity regime: 102 observations, average median excess return = 0.50%. High liquidity regime: 91 observations, average median excess return = -0.50%.
Style Skew	The variable had a positive relationship with alpha availability. When the dispersion between value and growth was large (positive or negative), excess returns were higher.	Style skew was used in 91 observations when liquidity was in the high regime (over 5%). It accounts for 27% of the contribution to R2.	3.5% is the threshold to differentiate large vs. small style skew regimes, given a high liquidity regime.	Large style skew regime: 54 observations, average median excess return = -0.20%. Small style skew regime: 37 observations, average median excess return = -0.90%.
Policy Uncertainty	The variable had a negative relationship with excess return. When uncertainty is high, active managers tended to deliver less alpha.	Policy uncertainty only was a significant predictor when liquidity was in the low regime (below 5%). The variable was used 102 of 193 observations (53% of the time). It accounts for 16% of the contribution to R2.	159 is the threshold to differentiate high vs. low policy uncertainty regimes under the low liquidity regime.	Low policy uncertainty regime: 90 observations, average median excess return = 0.7%. High policy uncertainty regime: 12 observations, average median excess return = -0.6%.

Non-U.S. Active Managers

Variable	Directional Impact	Interaction (Path dependencies)	Critical Values	Results
Style Skew	The variable had a negative relationship with alpha availability. Active managers tended to deliver greater alpha when the deviations between value and growth factors were not extremely large.	This is the most important factor that explains variation for secondary analysis. It accounts for 61% of the contribution to R2. Much like the concentration variables in Analysis 1, it is most powerful at extreme levels (very high skew is oberved with very low alpha availability).	11.5% is the maximum threshold to differentiate high style skew from moderate and 2.5% is the maximum threshold to differentiate moderate from low skew	Large style skew regime: 14 observations, average median excess return = 0.22%. Moderate style skew regime: 142 observations, average median excess return = 1.44%. Low style skew regime: 55 observations, average median excess return = 2.09%.
Size Skew	The variable had a positive relationship with excess return. When the dispersion betwwen cap weighted and equal weighted indice s is large, alpha availability was high.	Size skew only was a significant predictor when style skew was in the moderate regime (between 2.5% and 11.5%). The variable was used 55 of 211 observations (26% of the time). It accounts for 23% of the contribution to R2.	5% is the threshold to differentiate large vs. small size skew regimes under the low style skew regime.	Large size skew regime: 7 observations, average median excess return = 3.5%. Small size skew regime: 48 observations, average median excess return = 1.9%.
Policy Uncertainty	The variable had a positive relationship with alpha availability. When economic policy uncertainty is high, active managers tended to deliver greater alpha.	Size skew only was a significant predictor when style skew was in the low regime (below 2.5%). The variable was used 55 of 211 observations (26% of the time). It accounts for 23% of the contribution to R2.	115.9 is the threshold to differentiate high vs. low levels of policy uncertainty	High Policy Uncertainty regime: 107 observations, average median excess return = 1.58%. Low Policy Uncertainty regime: 35 observations, average median excess return = 0.99%.

Table 7 Cont'd

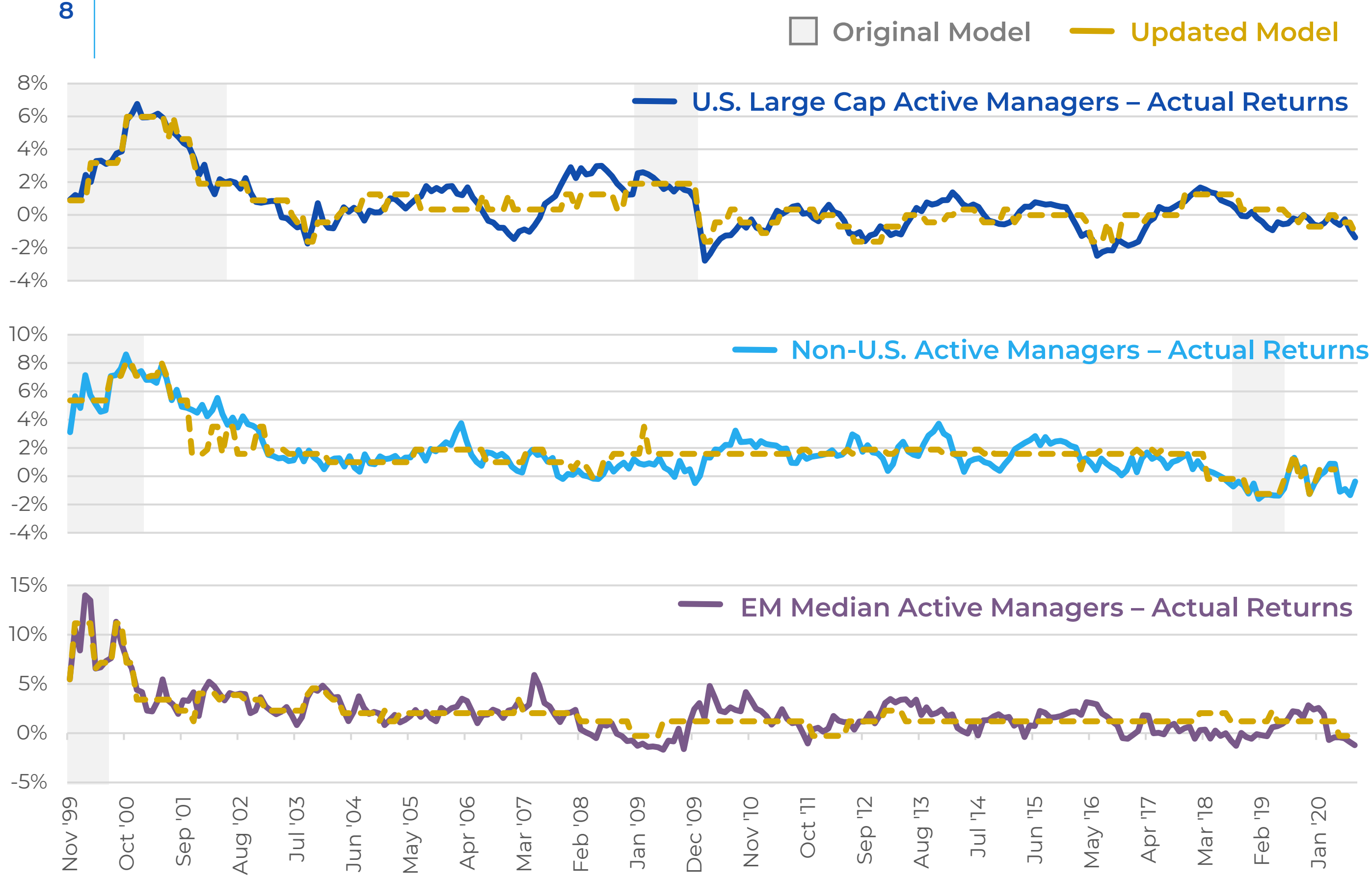
EM Active Managers

Variable	Directional Impact	Interaction (Path dependencies)	Critical Values	Results
Correlation	The variable always had a negative relationship with excess return. When stock correlation is relatively low, active managers tend to deliver greater alpha.	This is the most important factor that explains variation for secondary analysis. It accounts for 67% of the contribution to R2.	0.17 is the maximum threshold to differentiate high instrastock correlation from moderate and 0.11 is the maximum threshold to differentiate moderate from low correlation	Low correlation regime: 9 observations, average median excess return = 4.09%. Moderate correlation regime: 33 observations, average median excess return = 2.84%. High correlation regime: 195 observations, average median excess return = 1.34%.
Policy Uncertainty	The variable had a negative relationship with excess return. When uncertainty is relatively high, active managers tended to deliver less alpha.	Policy uncertainty was primarily considered when correlation was in the high regime (above 0.17). The variable was used 195 of 237 observations (82% of the time). It also played a lesser role in the 33 observations when correlation was moderate. It accounts for 26% of the contribution to R2.	98 is the threshold to differentiate high vs. low policy uncertainty regimes under the high correlation regime. (with a slightly lower 96 threshold under moderate correlation).	Low policy uncertainty regime: 51 observations, average median excess return = 2.2%.* High policy uncertainty regime: 144 observations, average median excess return = 1.0%.*

Low policy uncertainty regime (under moderate correlation) : 16 observations, average median excess return = 3.4%.
High policy uncertainty regime (under moderate correlation) : 17 observations, average median excess return = 2.3%.

Chart 8

Combined Model



Summary

The deeper level analysis, which isolated "balanced" markets, helped us understand alpha availability drivers during most periods.

U.S. Large Cap Active Managers

Periods of high liquidity were a significant headwind for U.S. active managers. This factor dominated the U.S. model, while not achieving significance in the other two models. This model's usage conforms with our prior logic; whenever there was an abnormal liquidity injection into the market, it lifted all boats and brought headwinds for active managers who rely on distinguishing between winners and losers. The liquidity factor was global, but due to the U.S. Dollar's status as reserve currency and the fact that the Fed was the first mover on most of the abnormal monetary events if the past 13 years, a disproportionate impact on U.S. managers is to be expected. Holding the liquidity level constant, active managers favored low policy uncertainty where their stock selection skill is more likely to transfer into alpha rather than overwhelmed by macro shocks. A dispersion in style factor performance also seems to create a favorable environment for active managers; it is important to note that the style skew threshold is quite low and only important when liquidity was high. We interpret this to mean that active managers could exploit modest factor trends, despite high liquidity.

Non-U.S. Large Cap Active Managers

The secondary model for Non-U.S. active managers was less insightful than the U.S. model. Some directional results are contrary to our prior expectations, such as Policy uncertainty having a positive relationship with alpha availability. **Chart 7** (on page 16) shows the periods in which these thresholds were reached. Since the Great Financial Crisis, Non-U.S. markets had policy uncertainty above the threshold set by the analysis. This should be no surprise given the macro backdrop; sovereign debt crisis, Brexit, Abenomics, etc. Secondly, the style skew variable was a significant driver of low alpha availability, albeit with a high threshold of 11.5% dispersion. This only captures the tail end of a multi-year growth, quality and momentum trend, which the Covid Crisis exacerbated in 2020. The takeaways are that Non-U.S. strategies are less sensitive to exogenous shocks to alpha availability outside of market skew (concentration, style and size).

Emerging Market Large Cap Active Managers

The Emerging markets model tells a very clean and logical story. A market environment that had relatively low stock correlations coupled with a stable macro backdrop (low policy uncertainty) was favorable for active managers. The typical process of active managers allocates based on company specific fundamentals and catalysts; it is no surprise that they would appreciate an environment with low correlation among stocks that is not overwhelmed by systematic or macro shocks.

Actionable Takeaways

Identifying periods of high and low alpha opportunity and the drivers of these periods is valuable to us in our role of selecting managers to build portfolios. Understanding these dynamics provide useful context for evaluating manager returns over a given time horizon as well as setting expectations for future returns. When we expect the level to be high, we can bias portfolios toward our highest active share managers and shade toward index-tracking when alpha availability is low. There are a few critical questions to think about as you consider the level of active risk you are seeking in your portfolio.

U.S. Alpha Availability

Regime Changes in Market Leadership

If you anticipate under-performance in heavily weighted U.S. stocks or industries, you should be allocating to highly active managers. For large cap U.S. stocks, high levels of concentrated losses have coincided with major regime shifts, with an abrupt change in sentiment toward prior market leaders. Much like predicting the end of a bull market, predicting the exact timing of regime shifts is difficult. We believe that it is best analyzed through the lens of conditional probability. Factors such as extreme valuation dispersions, price momentum performance, market sentiment, performance skew, factor crowding, diverging earnings estimates and credit spreads are all factors we will be analyzing in future work to analyze the conditional risk in various markets.

Liquidity and Policy Environment

Concentrated losses are relatively rare, after all, you can't reverse a trend without it having time to form. If you are uncertain or forecasting no change in the market regime, liquidity and the policy environment are the areas to focus on. Increasing certainty around policy and the economy favors active management, more so if the liquidity is not extremely loose.

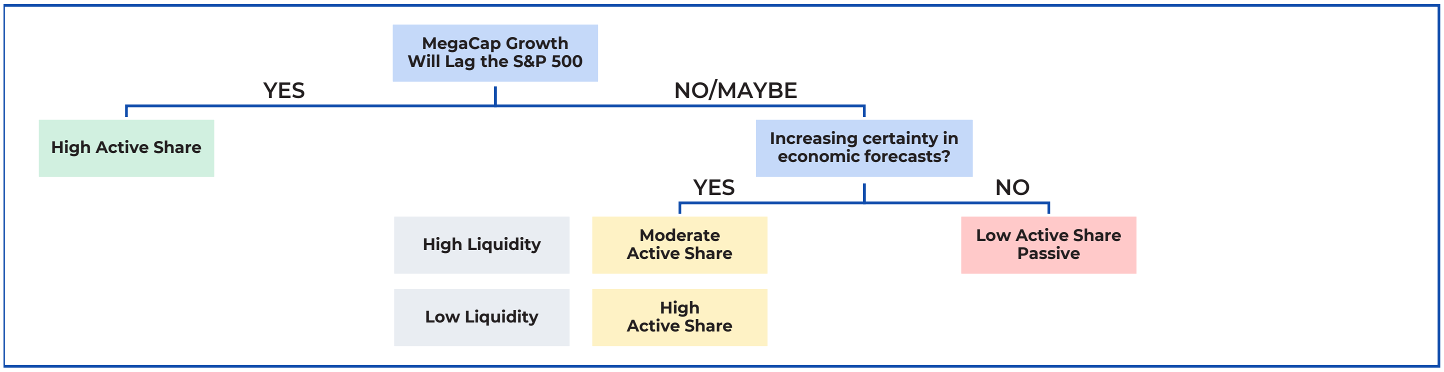
Current Environment for U.S. Active Managers

How do you feel about the stocks in **Table 8**? The under-performance of the stocks would lead us to a high level of concentrated loss in the S&P 500, which has proven to support alpha availability. This may seem trivial, but it is not. Of the 139 actively managed Large Cap Mutual Funds tracking the S&P 500 as of December 31, only 23% held Apple at market weight or higher. Similar numbers are found for the other 6 stocks on this list, which have led the market for the past few (you should give a number) years. If we see a sentiment turns against high quality (Tesla excluded) megacap growth stocks, active managers are likely poised to outperform the index significantly.

Table 8

Name	Weight	Sector
Apple Inc.	6.68	Information Technology
Microsoft Corporation	5.29	Information Technology
Amazon.com, Inc.	4.37	Consumer Discretionary
Facebook, Inc. Class A	2.07	Communication Services
Tesla Inc	1.68	Consumer Discretionary
Alphabet Inc. Class A / C	3.26	Communication Services

Chart 10



Non-U.S. Alpha Availability

Regime Changes in Market Leadership

Unlike the more efficient U.S. markets, active managers have a consistent edge relative to the index. The Alpha availability has cyclicality, but tends to be positve over any reasonable horizon. An environment with large and concentrated index losses within MSCI EAFE is the most supportive of active management. The MSCI EAFE index is less concentrated than U.S. or Emerging Market indices. Large, concentrated losses in this benchmark are more likely to be driven by regime changes in sector, region or style than individual stock sentiment. Our future work to forecast the likelihood of concentrated losses will explore currency, sovereign debt, and cross region EPS growth in addition to the factors mentioned for the U.S. market.

Current Environment for Non-U.S. Active Managers

How do you feel about the stocks in **Table 9**? Underperformance of these stocks would lead us to a high level of concentrated loss in the MSCI EAFE, which has proven to support alpha availability. Unlike U.S. and EM markets, the EAFE index is much less concentrated in names, sector or style, making a forecast of concentrated losses even less certain.

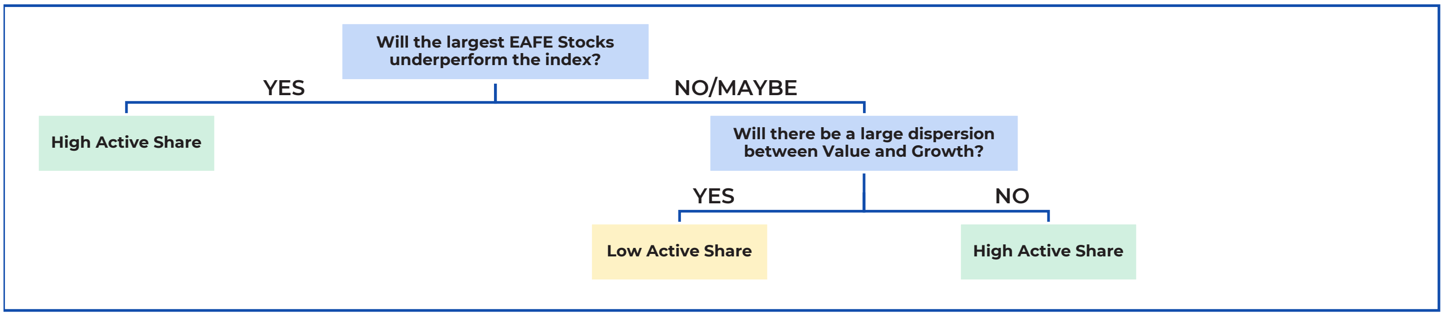
Table 9

Name	Weight	Sector
Nestle S.A.	2.15	Consumer Staples
Roche Holding Ltd	1.55	Health Care
Novartis AG	1.33	Health Care
ASML Holding NV	1.31	Information Technology
LVMH Moet Hennessy Louis Vuitton SE	1.10	Consumer Discretionary
Toyota Motor Corp.	1.03	Consumer Discretionary
Unilever PLC	1.00	Consumer Staples
AIA Group Limited	0.94	Financials
SAP SE	0.87	Information Technology
AstraZeneca PLC	0.83	Health Care

Style Skew

Allocators should favor lower active share and passive managers when they forecast a very strong style skew in the coming year. The EAFE and ACWI ex U.S. Value and Growth indices' structure is less concentated in names and sectors than their U.S. and EM counterparts, which makes this forecast more complicated.

Chart 11



EM Alpha Availability

Early in our study we mention that periods when the EM index had experienced concentrated gains[4] coincided with high relative returns for active managers. However, the EM markets and investment strategies have evolved to the point that we think it is prudent to update the analysis focusing on more recent time periods. Since 2003, periods with concentrated index gains have been difficult for active managers to generate alpha. As an allocator, we prefer the simple and logical path. When the largest benchmark names are dramatically outperforming the average stock, owning the index or a basket of megacap stocks is an efficient strategy. Within the EM universe, active managers have done well in all but the most skewed markets, but some secondary factors are useful in deciding the optimal level of risk taking.

Current Environment for EM Active Managers

How do you feel about the stocks in **Table 10**? EM active managers have only underperformed collectively when the index has highly concentrated gains. Concentration in the EM index is very similar to the U.S. markets with Mega-cap high quality growth companies dominating the index weights. Continued strength in these names would favor low active share managers and index funds.

Table 10

Name	Weight	Sector
Taiwan Semiconductor Manufacturing Co., Ltd.	5.89	Information Technology
Alibaba Group Holding Ltd.	5.59	Consumer Discretionary
Tencent Holdings Ltd.	5.31	Communication Services
Samsung Electronics Co., Ltd.	4.52	Information Technology
Meituan Class B	1.74	Consumer Discretionary
Naspers Limited Class N	1.14	Consumer Discretionary

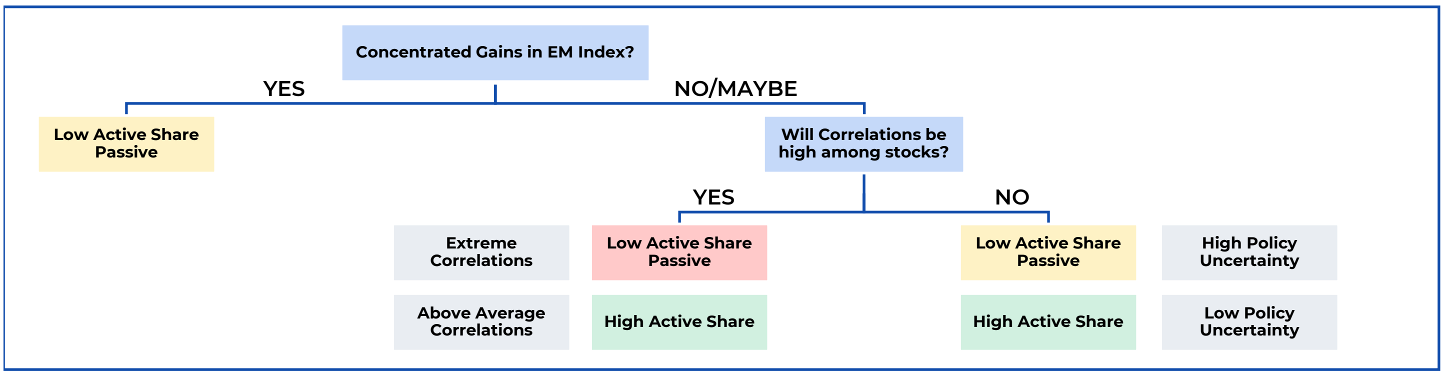
[4] The concentrated gain variable was a dominant positive contributor to alpha availability in this study, but all observations occurred prior to 2001 which is before Chinese and Taiwanese equities were fully added to the universe. Part 3 of our analysis shows that Concentrated gains have been a dominant negative contributor from 2003 onward. We believe the high overlap between concentrated gains and loss variables for the EM index lead to the conflicting results of this study.

Policy Uncertainty and Correlation

The following questions will be significant in all but the most skewed equity markets. Do you expect the clarity around economic policy and forecasts to become more certain? The Policy Uncertainty Index is GDP weighted, so what happens in China dominates the index's direction. Highly uncertain times have lowered the level of alpha availability, with active managers providing lower albeit positive alpha.

Absent strong market skew, the only environment in which allocators should favor passive EM strategies is when there is extreme correlations among stocks, coupled with uncertain economic policy. The majority of those observations came in the 1st and 2nd quarter of 2020 as the Corona Virus' uncertainty was at a fever pitch.

Chart 12



Conclusion

The alpha availability in a market is a useful tool in determining the risk posture of manager selection choices (Full Index replication through 100% active share). We have shown what factors contribute high and low alpha availability in U.S., Non-U.S. and Emerging Market universes. Understanding the environmental drivers will allow allocators to make more informed decisions about the type of active risk to target in their manager allocations.

Part 3 of our study, we will look at fundamental vs. quantitative managers. Do the two approaches have the same sensitivity to the systematic factors driving alpha availability?