

# Alpha Availability

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

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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*”).

### Authors



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



**Bin Cheng, CFA**  
Quantitative Research Analyst

### 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.*

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### Part 3

## Alpha Availability Based on Investment Approach

In **Part 2** of our study, we uncovered the systematic factors driving alpha availability across regions. Our experience as allocators tells us that a manager's investment approach is also an essential factor in understanding the availability of alpha for a strategy.

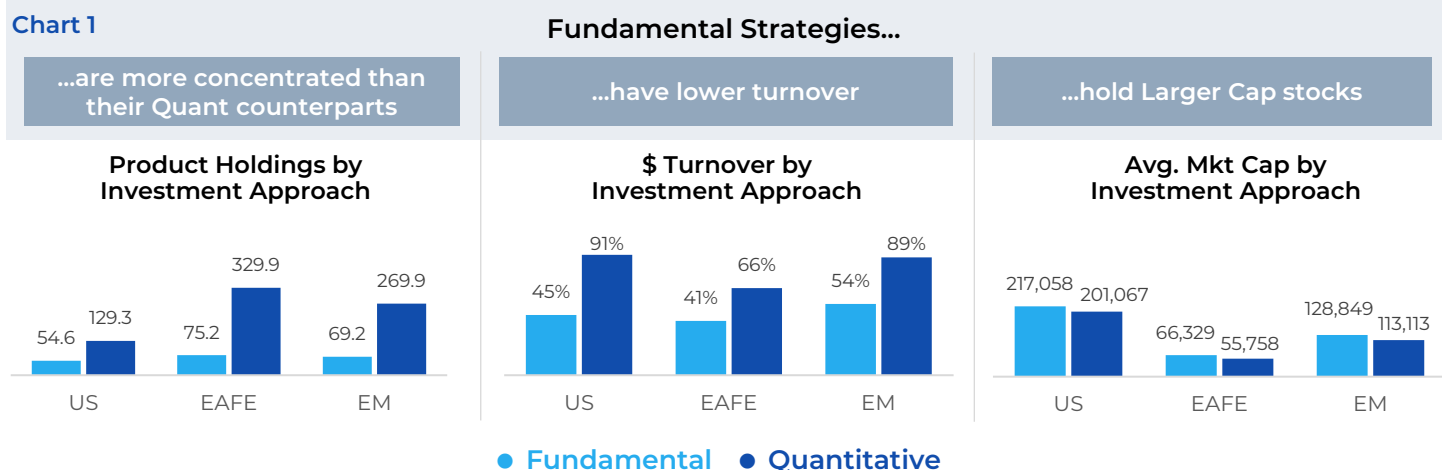
Fundamental and Quantitative approaches are very broad categorizations that delineate the strategy of a manager based on the use of quantitative models in the selection of investments. The reality is that almost all managers use some level of quantitative modeling in their process. Even the "old school" fundamental stock picker will often use a quantitative screen to help cull their universe to a manageable level or use statistical risk models during portfolio construction. When evaluating a manager, we consider a pure quantitative manager as someone who systematically selects stocks and builds portfolios without human intervention. In practice, very few managers are 'pure' quants, and live in the shades of gray between the extremes. For purposes of this analysis, we utilize the "primary investment approach", which managers have reported to Evestment. We combine "Quantitative" and "Combined" approaches. Based on our knowledge of the managers, most managers listing "Combined" are heavily skewed toward systematic implementation.

As we analyze these 2 approaches, it is important to note that this analysis is not trying to opine on their relative merits. We are analyzing the common traits portfolios using the same approach tend to share and what that means for when they will most successful generating excess return.

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Chart 1



Evestment Monthly Database, MPI stylus, Xponance

2,549 strategies in total. All Large Cap and All Cap Separate Account Strategies with valid data for 'product holdings' and Net Assets > 0 in the 3 regions. 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)

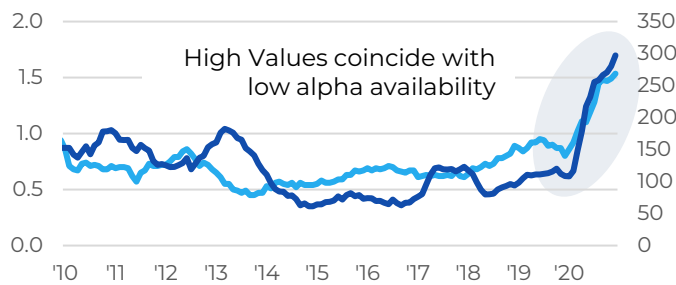
## Alpha Availability: Part 3

None of this information is surprising. Fundamental managers are searching for very high conviction ideas and holding them for a long time. Quantitative strategies want to identify many smaller edges, and maximize the risk adjusted return potential through diversification and more frequent rebalancing. The size bias of Fundamental managers is less clear. One possibility is that quantitative back-tests have been more successful identifying alpha opportunities in relatively less followed names, biasing portfolios away from megacap stocks. Accordingly, small cap premium may also impact backtests, depending on the time horizon. The portfolio construction mechanics of quant managers also tends to be biased against holding megacap stocks at or above market weight. To illustrate the bias, consider a hypothetical decision on whether to make a 7% allocation to Apple or a basket of technology stocks. Portfolio optimization models typically focus on maximizing alpha potential relative to the tracking error of a portfolio. If alpha is equal, the model will favor allocating to a basket of stocks vs. an overweight position in Apple, in order to diversify idiosyncratic risk (and lower projected tracking error).

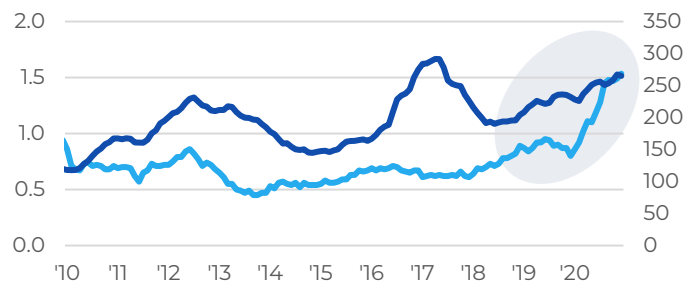
This three-part research series was also catalyzed by ours and our clients' observations of the recent performance challenges of quant managers. In a separate research note entitled "A Challenging Environment for Quant Strategies"<sup>1</sup> our colleagues identified concentrated market leadership and economic policy uncertainty as particularly challenging for U.S. Large Cap Quant managers. Our analysis confirms this perspective.

### Chart 2

#### Key Factors Impacting U.S. Quant Strategies

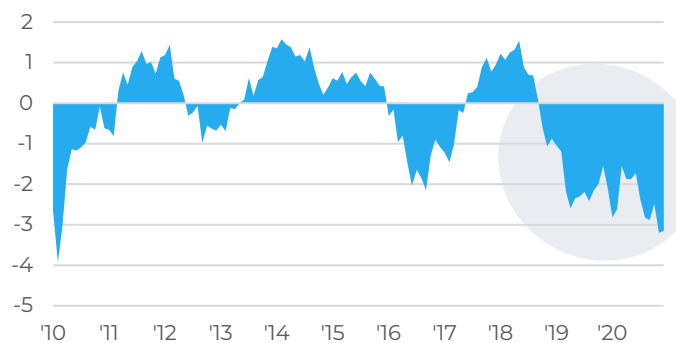


#### Key Factors Impacting Non-U.S. Quant Strategies

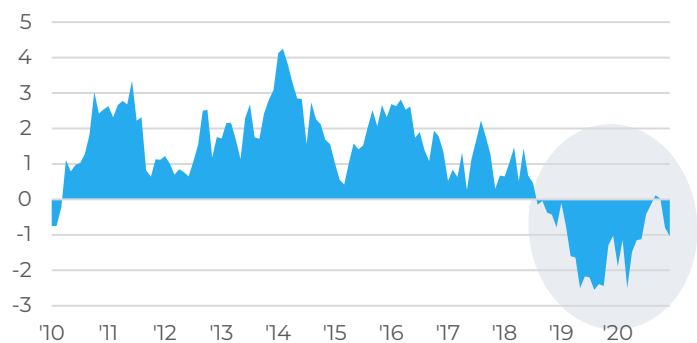


— Concentrated Gains (Left) — Policy Uncertainty (Right)

#### U.S. Quant Managers Median Excess Return Trailing 12m



#### Non-U.S. Quant Managers Median Excess Return Trailing 12m



Evestment Monthly Database, MPI stylus, Xpounce

All Separate Account Strategies with 36 months of reported gross returns between 1/2003 -12/2020 and primary investment approach of Quantitative or Combined. Universes: (U.S. = All U.S. Large Cap Equity, Non-U.S. = All EAFE Equity and All ACWI ex-U.S. Equity)

<sup>1</sup> <https://www.xpounce.com/a-challenging-environment-for-quant-strategies/>

## Alpha Availability: Part 3

### Analysis

In this analysis we used the same regression tree analysis as our prior work and tested the variables described in **Part 2**<sup>2</sup> against 2 subgroups of managers based on the stated primary investment approach. We limited the analysis to 1/2003 -12/2020 to avoid misclassifying strategies that have evolved from one approach to the other over time. The results show a clear difference with respect to how factors impact alpha availability. The explanatory power of the split models was in line with the aggregate model. **Table 1** characterizes the analyzed universes for U.S. Large Cap; Non-U.S. Large Cap Developed Market and Emerging Market managers.

**Table 2** summarizes the results of our regression tree analysis. The numbers in the table represent the relative explanatory power of that factor, while the color represents the directional impact (Green for a positive impact on Alpha Availability, Red for a negative relationship). The full regression trees, with the critical 'cutoff' values can be seen in the appendix.

**Table 1** | **Data Summary**  
1/2003 – 12/2020

		No. of Products	Median 12m Excess	% Positive 12m Periods
<b>U.S. Large Cap</b>	Quant	394	-0.1%	49.0%
	Fundamental	825	0.4%	67.7%
<b>Non-U.S.</b>	Quant	71	1.3%	71.9%
	Fundamental	169	1.1%	82.3%
<b>Emerging Markets</b>	Quant	83	0.1%	54.2%
	Fundamental	146	1.5%	79.2%

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) Quant = Primary Approach of "Quantitative" or "Combined"; Fundamental = Primary Approach of "Fundamental"

**Table 2** | **Analysis and Results**

#### U.S. Large Cap Managers 2003-2020

	All	Quantitative	Fundamental
Concentrated Gains	-	40.0%	-
Concentrated Losses	40.5%	8.1%	51.3%
Policy Uncertainty	-	25.8%	18.7%
Style Skew	-	-	-
Size Skew	-	-	-
Sector Skew	22.0%	-	-
Correlation	-	18.6%	0.4%
Liquidity	37.4%	7.4%	29.6%
R-Squared	43%	41%	42%

#### Developed Non-U.S. Large Cap 2003-2020

	All	Quantitative	Fundamental
Concentrated Gains	14.2%	-	2.5%
Concentrated Losses	58.1%	40.9%	46.4%
Policy Uncertainty	27.7%	17.0%	24.4%
Style Skew	-	-	12.0%
Size Skew	-	-	-
Sector Skew	-	17.6%	-
Correlation	-	-	14.8%
Liquidity	-	24.1%	-
R-Squared	52%	52%	46%

#### Emerging Market Managers 2003-2020

	All	Quantitative	Fundamental
Concentrated Gains	45.1%	59.8%	21.3%
Concentrated Losses	-	3.2%	22.6%
Policy Uncertainty	11.3%	24.6%	3.1%
Style Skew	2.8%	-	-
Size Skew	-	-	-
Sector Skew	40.4%	10.7%	52.4%
Correlation	0.4%	1.7%	0.7%
Liquidity	-	-	-
R-Squared	41%	43%	31%

<sup>2</sup> <https://www.xponance.com/a-challenging-environment-for-quant-strategies/>

## Alpha Availability: Part 3

### U.S. Large Cap Manager Universe

1/2003 - 12/2020

Mean Manager Return (average)	
Quantitative Managers	0.02%
Fundamental Managers	0.23%

	Quant Strategies	Fundamental Strategies
<b>Best Markets</b>	When concentrated gains are relatively low (40% of the time), the median quant manager has +0.65% excess return. In the 65% of those observations that liquidity was also low, they outperformed by 0.91%.	During the 10% of markets when concentrated losses are extreme, the median Fundamental manager has +2.1% excess return. During all other markets, liquidity is the primary factor. When liquidity is roughly below average (53% of the time), fundamental strategies outperform by 0.53%.
<b>Worst Markets</b>	When concentrated gains are relatively high (60% of the time), the median quant managers had -.38% excess return. In the 5% of observations that Policy Uncertainty was also high, Quant managers underperformed by 2.66%.	When concentrated losses are not extreme (90% of the time), fundamental managers do poorly when liquidity is higher than average (47% of the time), with average excess returns of -0.50%.

### Developed International Manager Universe

1/2003 - 12/2020

Mean Manager Return (average)	
Quantitative Managers	1.22%
Fundamental Managers	1.21%

	Quant Strategies	Fundamental Strategies
<b>Best Markets</b>	When concentrated losses are not extremely low (94% of the time), the median Quant manager has +1.41% excess return. When you further exclude the periods with the highest 20% of liquidity returns increased to +1.70%.	When concentrated losses are not extremely low (94% of the time), the median Quant manager has +1.34% excess return. From that point, fundamental strategies had +1.56% excess when policy uncertainty was reasonably high (70% of the time). These managers also saw incremental increases to return when sector and style skew was low.
<b>Worst Markets</b>	During periods with extremely low levels of concentrated losses (6% of the time), the median quant manager has -1.23% excess return. When concentrated losses are not extremely low, top 20% liquidity environments cut gains to +0.34%	During periods with extremely low levels of concentrated losses (6% of the time), the median fundamental manager has -0.39% excess return. When concentrated losses are not extremely low, fundamental managers struggled when policy uncertainty was low (bottom 30%) and there was style skew, averaging only +0.58% excess return.

### Emerging Market Manager Universe

1/2003 - 12/2020

Mean Manager Return (average)	
Quantitative Managers	1.23%
Fundamental Managers	1.49%

	Quant Strategies	Fundamental Strategies
<b>Best Markets</b>	When concentrated gains is outside of either extreme (85% of all observations) policy uncertainty is the most powerful predictor of quant excess returns. Bottom quartile readings on policy uncertainty have coincided with 2.42% excess return for the median quant manager. Periods with when concentrated gains were extreme, were associated with extreme performance. The 10 periods with the lowest levels of concentrated gains saw 4.23% excess returns for the median quant manager.	When correlations were below the top decile, the median fundamental manager had +1.65% excess return. When you exclude top decile periods for concentrated gains, the excess increased to 1.79%.
<b>Worst Markets</b>	When concentrated gains is outside of either extreme (85% of all observations) policy uncertainty is the most powerful predictor of quant excess returns. Observations above the bottom quartile on policy uncertainty have coincided with 0.92% excess return for the median quant manager. Periods with when concentrated gains were extreme, were associated with extreme performance. The 24 periods with the highest levels of concentrated gains saw -0.92% excess returns for the median quant manager. Returns further deteriorated when correlations were high.	When correlations were in the top decile, the median fundamental manager had -0.46% excess return. During periods of lower correlation, during top decile periods for concentrated gains, the excess increased to 0.33%.

### Summary of Analysis

#### U.S. Large Cap Active Managers

Levels of market concentration remained an important indicator for alpha availability, but the two approaches have unique exposures. Quantitative managers were negatively impacted by anything more than modest levels of concentrated gains in the index while fundamental managers were not impacted. This is consistent with our earlier discussion on the bias of systematic risk models to prefer diversification over concentrated positions. A fundamental manager with high conviction in a large index constituent is more likely to have a large overweight to that stock. Both approaches tended to generate greater alpha when large concentrated losses happened within the market. Lower levels of liquidity (bottom 50%) benefited all active managers, with fundamental managers being more sensitive to its effect. Fundamental managers were less challenged by high levels of Policy uncertainty. Policy Uncertainty only impacted quant strategies when it is very high, and it was associated with very poor outcomes. It's interesting to observe that fundamental managers favored high policy uncertainty under large concentrated losses regime; it seems that fundamental manager's investment insights on market dynamics could during periods of stress have added incremental value into their process but it's important to note that this specific regime only had 19 observations.

#### Non-U.S. Large Cap Active Managers

Market concentration had a significant impact on both Non-U.S. quant and fundamental managers' alpha availability. Both approaches thrived when concentrated losses are not extremely low. Holding the concentrated losses factor constant, quant managers unsurprisingly tended to produce greater alpha when correlation among stocks was low, as this environment will favor a portfolio of well diversified stock specific risks over more correlated systematic risk. On the other hand, holding the concentrated losses factor constant, fundamental managers tended to generate greater alpha when there was less skew in the sector and style factors. This follows our experience with fundamental managers, whereby the outsized returns attributable to sectors and style typically swamp stock specific alpha. The observation that Fundamental managers outperformed when policy uncertainty is high needs more analysis. As we mentioned in [Part 2](#), this factor has been persistently high in recent years outside of U.S. markets.

#### Emerging Market Large Cap Active Managers

For the EM model, it is important to note that the "extreme values" in critical variables occurred early in the analysis when the EM markets had dramatically different structures. In these highly dynamic markets, it is always a challenge to find enough observations to have a thorough model without including periods in which the markets are unrecognizable. Our analysis suggests that the correlation between stocks in the index impacted fundamental EM managers more than any other manager archetype, including quant EM managers. Emerging Market stocks typically allow for a wide variety of differentiated viewpoints given the relative independence of regional economies and larger percentage of locally focused companies, compared to developed market universes. When those independent risks are ignored by the market in high correlation regimes, it is reasonable that fundamental managers would add little alpha. Quant managers were more sensitive to policy uncertainty and extreme gain and loss concentration levels, which is consistent with previous analysis and regions.

### Actionable Takeaways

Our research confirmed our colleagues conclusion (see “A Challenging Environment for Quant Strategies”) that concentrated market leadership and economic policy uncertainty negatively impacted the performance of U.S. and Non-U.S. quant managers in recent years. The market conditions that led to the outsized underperformance of quant managers will eventually abate or reverse. For our clients’ portfolios, we have intentionally avoided making a call on the timing of this particular outcome; but rather we have reduced our allocation to quant strategies based on the heightened level of economic policy certainty resulting from the Covid-19 crisis). Finally, while our findings regarding Emerging Markets managers are intuitive and consistent with our experiences of having allocated to such managers for well over a decade, as observed previously, we recommend caution in your interpretation of our EM model because of changes in the structure of EM markets during the analysis period.

### Appendix

#### Regression Tree Summary and Results

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:

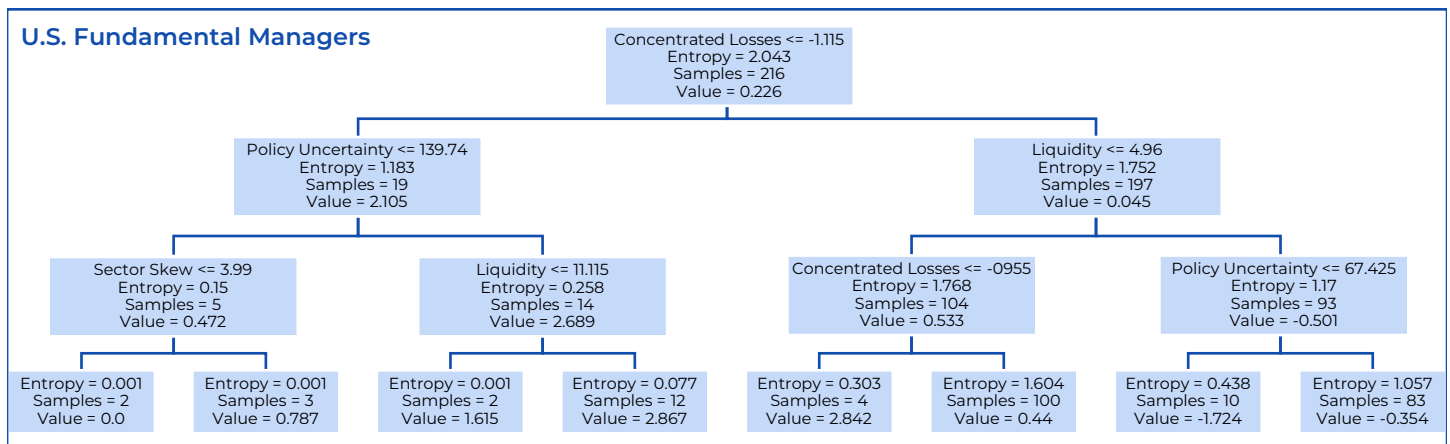
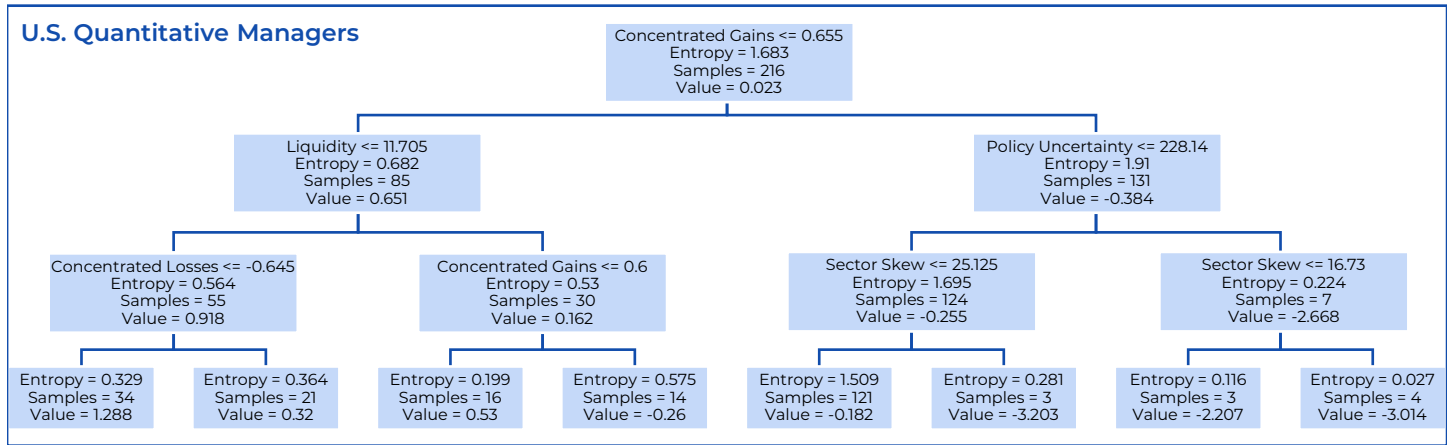
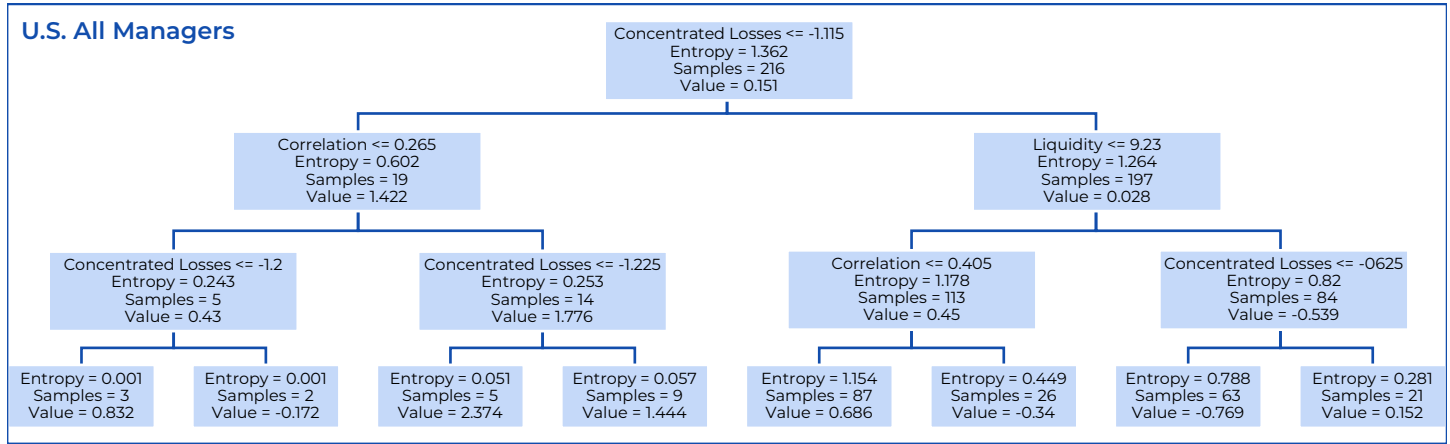
1. It accommodates nonlinear relationships. The regression tree methodology does not expect the data to be linear.
2. It provides the relative importance of variables as a straightforward output. The output gives us a clear understanding of the model drivers in ranked order.
3. The outcomes can be interpreted in a clean and straightforward format. It helps to understand the model and identify the underlying story behind the data.
4. 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.

See regression tree results on pages 8-10.

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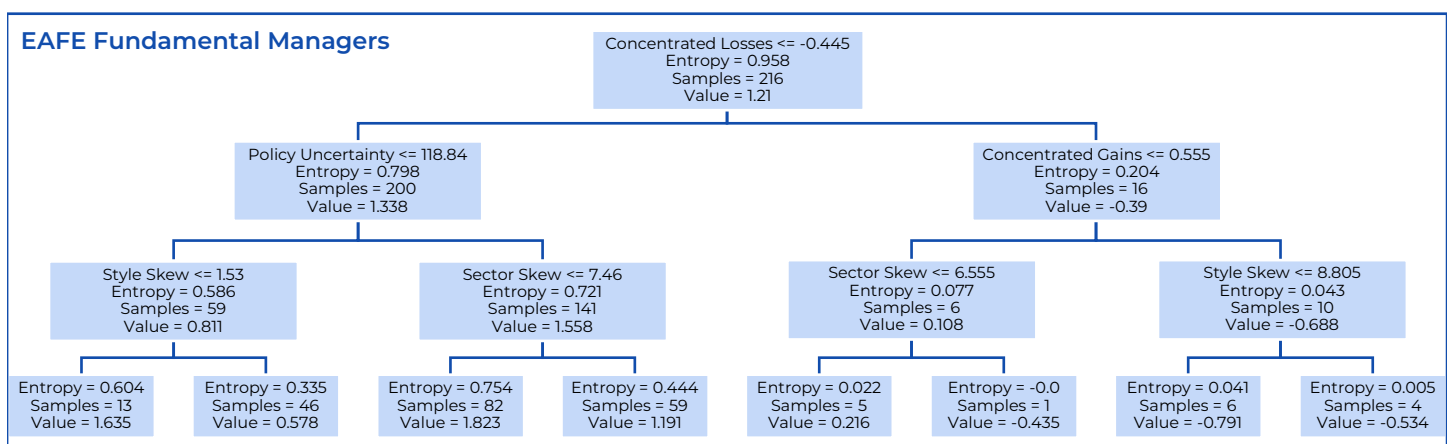
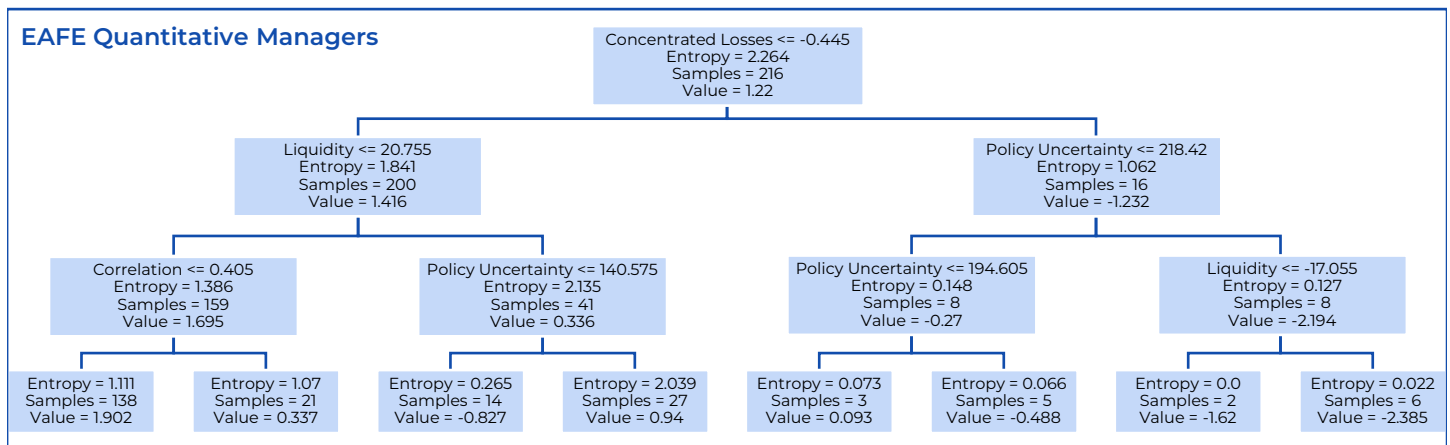
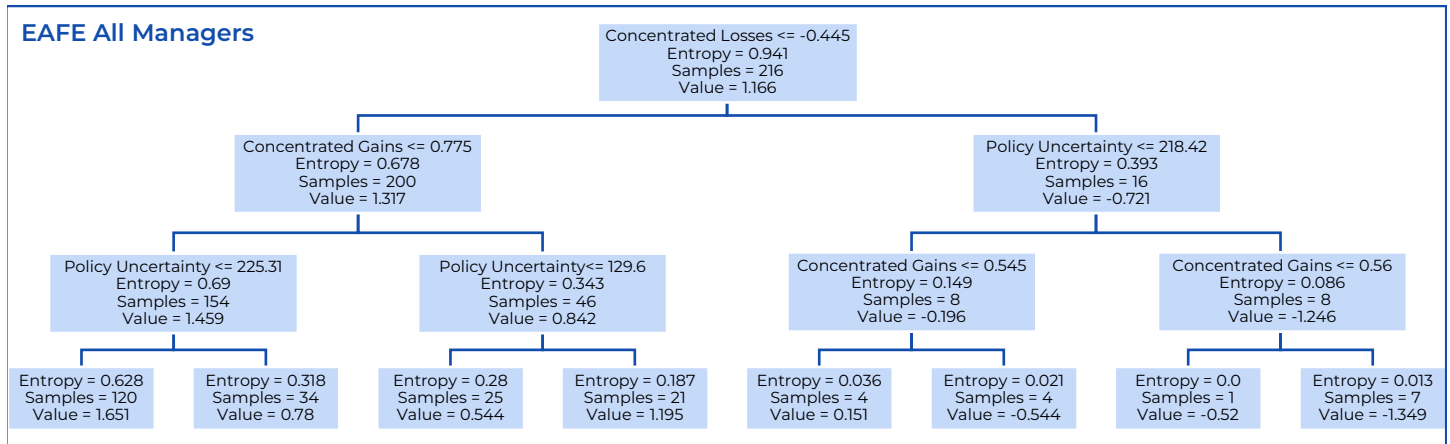
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# Alpha Availability: Part 3





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