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Essentia Analytics (www.essentia-analytics.com) is the leading provider of behavioral data analytics and consulting for professional investors. Led by a team of experts in investment management, technology and behavioral science, Essentia combines next generation data analytics technology with human coaching to help active fund managers measurably improve investment decision-making. Providing daily analysis on over $250 billion in assets, Essentia helps both short and long-term professional investors mitigate bias, maintain investment discipline and achieve better performance.

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# The Alpha Life Cycle: New Insight into Investment Alpha and How Portfolio Managers Can Sustain It

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## KEY FINDINGS

- Excess return attributable to manager decision-making at the position level (e.g., timing, sizing, scaling) has a distinct and persistent life cycle. It tends to accumulate in the early phase of an investment and decay over time—often precipitously.
- On average, positions are held too long, leading to a peak-to-exit negative portfolio impact of 7 basis points per position.
- While managers, on average, tend to hold their positions too long, the article identifies a significant window of opportunity for managers to act while their positions are still producing alpha in excess of their fees.

## ABSTRACT

In this article, the objective is to validate and better understand an effect of return generation at the position level that has long been assumed but never demonstrated: that return generation has a life cycle—a beginning, middle, and end—and that investors often hold on to positions too long, potentially diminishing whatever excess returns they were able to generate early in the life cycle. This analysis examines roughly 10,000 episodes (i.e., full cycles of a given position from first entry to last exit) across 43 active equity portfolios over 14 years.

Alpha is the measure of a portfolio manager's ability to add value beyond the effect of the overall market, and it remains the preeminent performance metric when attempting to measure skill. In an environment where many investors perceive low-cost index funds as offering better overall returns than their actively managed counterparts, the ability to assess a given manager's alpha (and the capability for active managers to contribute maximum alpha to their portfolios) is more critical than ever.

To make that assessment, we must first understand the characteristics of excess return on a position-by-position basis—what we are terming **position-level alpha.**

With that in mind, we set out to validate and better understand an aspect of position-level alpha that has long been assumed but never demonstrated: that it has a life cycle—a beginning, middle, and end—and that investors often hold on to positions too long, potentially diminishing whatever excess returns they were able to generate early in the life cycle.

Our analysis examines roughly 10,000 episodes (i.e., full cycles of a given position from first entry to last exit) across 43 portfolios over 14 years. The results demonstrate what we suspected: there is a clear life cycle to position-level alpha that, in general, starts strong and fades with age.

What surprised us is the magnitude of this effect: the average episode's alpha trajectory—as measured by cumulative excess return on investment (ROI) over the nominated index of the portfolio—followed an inverted horseshoe pattern and finished with a loss of over 2%.

We describe our methodology for this research in detail. While our research focuses on validating and quantifying the alpha life cycle itself, we also present some thoughts on *why* position-level alpha tends to behave as it does. We view it as a classic example of the *endowment effect*, one of the most common investor behavioral biases, at work.

In addition, although the alpha life-cycle diagram is not pretty, the good news is the generally significant period of outperformance before the tide shifts, demonstrating the value that active managers can add above indexed portfolios. Managers can and do contribute meaningful sustained alpha when they exercise discipline in their exit timing and avoid the biases that can lead to holding positions too long; we offer some thoughts on how to achieve such results in our conclusion.

## METHODOLOGY AND ASSUMPTIONS

### Position-Level Alpha

To analyze the performance of individual stocks relative to a benchmark over time, we define a measure that we call position-level alpha. This measure is a simple deconstruction of traditional alpha (i.e., excess return at the portfolio level; or portfolio performance versus benchmark performance) into its core constituent elements: that is, the difference between the return of the individual *positions* in a portfolio and the return of the benchmark index for that portfolio. Our analysis tallies the daily position-level alpha over the full term of each holding in each portfolio studied, producing clear alpha life-cycle plots for each position established by the managers in our universe.

### Sampling and Trimming

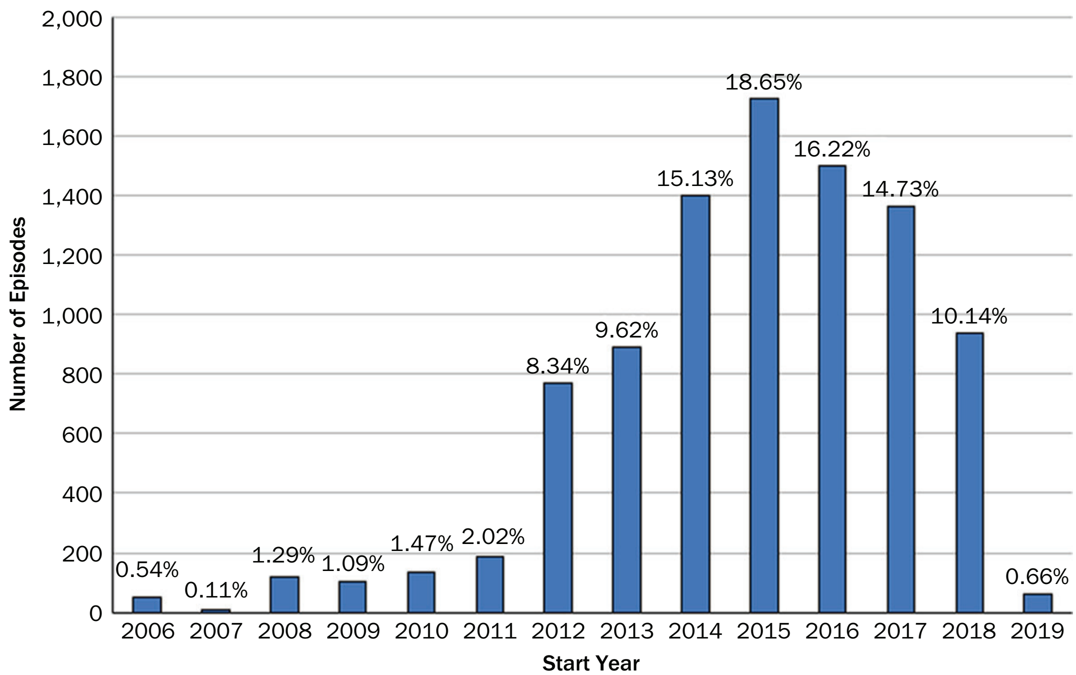
For this study, we analyzed detailed trade data from 2005–2019 in 43 equity portfolios of clients of Essentia Analytics (Appendix A includes the full universe of portfolios). The total number of episodes—each representing a single investment from the opening to the final trade—in this data set, over all portfolios, is 14,058. An episode is a single investment in a single equity instrument from the opening to the final closing trade. Each episode is constructed from our data set, which contains the date and price of every trade and the daily end-of-day holding quantity for every holding in every portfolio. Market data for each episode (e.g., the end-of-day prices and the end-of-day price of the nominated benchmark of the portfolio) are obtained from a well-known tier 1 third-party market data supplier.

All episodes that remained open at the close of the sample period are omitted. Also, we remove any episodes less than 20 business days long, leaving a final sample of 9,254 episodes of varying lengths ($\mu$ = 257; $\sigma$ = 319; MAX = 2,638). The mean number of episodes per portfolio is 215, with a standard deviation of 207. The smallest number of episodes in a given portfolio is 23, and the largest is 1,208.

Before conducting the main analyses, we investigate the nature of the episodes within our data set. Specifically, we identify the start year and length of each episode (Exhibit 1 and Exhibit 2, respectively).

**EXHIBIT 1**

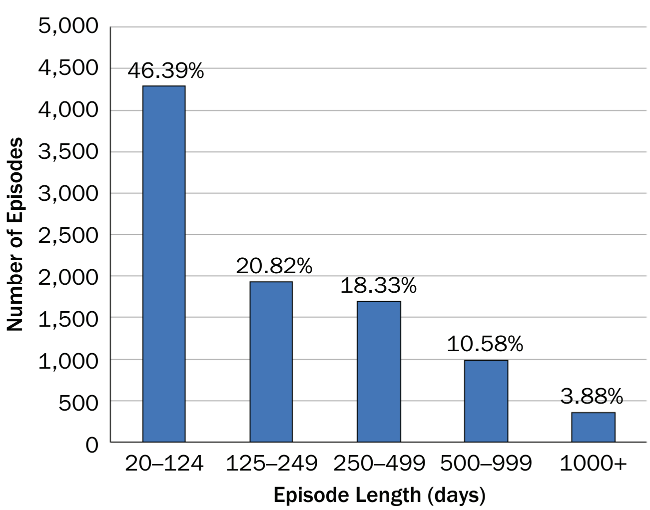
**Number of Episodes Opened in Each Year**




**NOTE:** The value above each bar represents the percentage of the total number of episodes starting in that year.

**EXHIBIT 2**

**Frequency of Different Episode Lengths within the Data Set**




**NOTE:** The value above each bar denotes the percentage of the data set within that episode length bound.

From these plots, it is clear that the majority of episodes within this data set (92.84%) begin between 2012 and 2018. Over all the data, the majority of episodes (85.54%) are less than 500 business days long. Therefore, our analysis is most pertinent to episodes with these qualities.

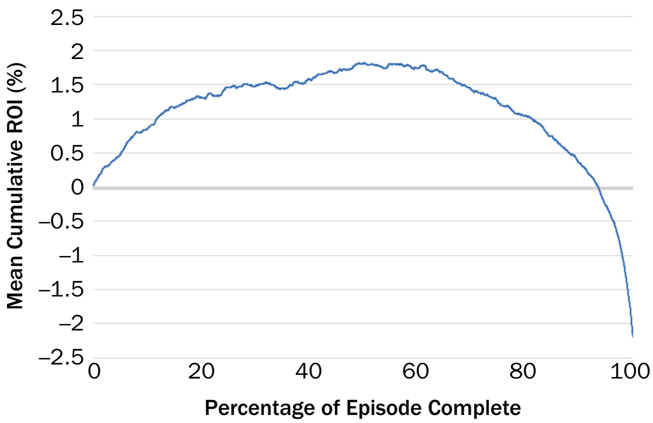
### Preprocessing and Interpolation

For each episode in each portfolio, we compute the cumulative relative impact (RI) and cumulative relative ROI. The RI is defined as the relative profit of that episode on that day divided by the absolute amount invested in the portfolio on that day (relative profit is the total increase in value of the investment on that day minus a hypothetical investment of the same amount in the benchmark). Similarly, ROI is defined as the relative profit on that day divided by the absolute total capital invested in that stock on that day.

As illustrated in Exhibit 2, the episodes in this data set vary considerably in length. Although the episodes may have similar life cycles, the cycles may occur over variable time periods. Therefore, to make the episodes comparable for analysis, we normalize them temporally. Each episode other than the largest episode in the data set is interpolated so that it now possesses the same number of data points as the largest episode. Time is then converted into a percentage of the episode completed.

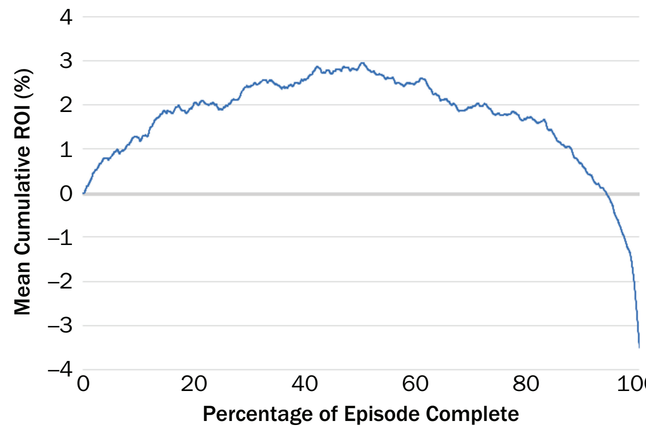
### EXHIBIT 3

**Grand Mean of Cumulative Relative ROI over All Episodes**




### EXHIBIT 4

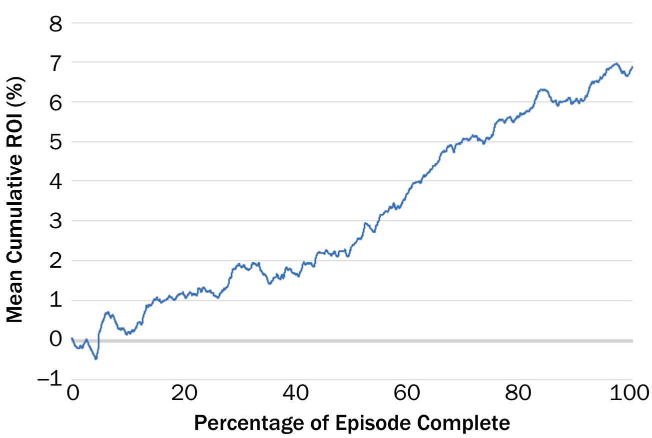
**Mean Cumulative Relative ROI of a Portfolio Demonstrating the Round Tripper Trend**




**NOTE:** This trend is similar to that of the grand mean plot of the same measure: a concave polynomial that demonstrates a progressive rise and then fall in alpha.

### EXHIBIT 5

**Mean Cumulative Relative ROI of a Portfolio Demonstrating the Linear Accumulator Trend**




**NOTE:** This trend is characterized by a positive linear gradient.

## Analysis and Observations

Our main analyses are computed using the mean of each of our measures at each episode percentage for each portfolio. This approach enables us to easily inspect the trends that are most applicable to each portfolio manager's data as a whole.

Before modeling the data set, a graphical inspection of each portfolio's measures and the grand mean across all portfolios are assessed to guide the functions to which we fit the data.

Our inspection of cumulative relative ROI reveals that the position-level alpha accumulation may follow one of several trends. When inspecting the grand average, the data follow a concave polynomial (inverted horseshoe) shape (Exhibit 3). At the portfolio level, the data often display this shape or a partial version of this shape. The exception to this rule is when the data follow a positive linear gradient. Overall, we find four subtypes of the life cycle of an episode, which we call, respectively, the "round tripper" (Exhibit 4), "linear accumulator" (Exhibit 5), "hopeless romantic" (Exhibit 6), and "coaster" (Exhibit 7).

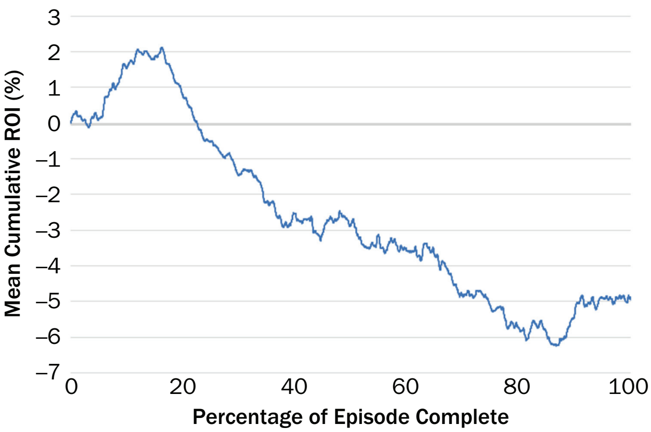
Because of these trends, our decision is to fit a quadratic function to cumulative relative ROI. Similarly, cumulative RI's grand mean plot (Exhibit 8) best fits a concave polynomial, so we choose to fit a similar function to this measure. Both models are fitted using maximum likelihood estimation.

Each of these measures is entered into its own respective random slope mixed-effect model. Both measures are predicted by the fixed effects of episode percentage and episode percentage squared, with a random effect of portfolio. Formally, the functions of these models follow the formula

$$y = ax^2 + bx + c + \varepsilon \tag{1}$$

## EXHIBIT 6

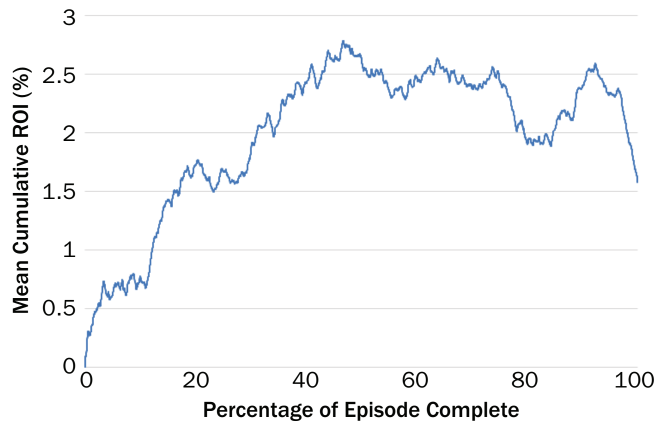
### Mean Cumulative Relative ROI of a Portfolio Demonstrating the Hopeless Romantic Trend




**NOTE:** This trend is characterized by an initial short-lived increase in cumulative relative ROI followed by a progressive decline for the remainder of the episode.

## EXHIBIT 7

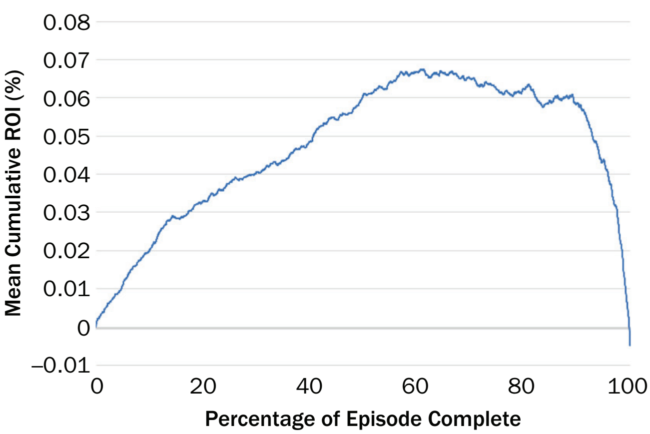
### Mean Cumulative Relative ROI of a Portfolio Demonstrating the Coaster Trend




**NOTE:** This trend is characterized by an initial rise in cumulative relative ROI that leads to a period of neither gain nor loss.

## EXHIBIT 8

### Grand Mean Cumulative RI for All Episodes Relative to the Percentage through Episode




**NOTES:** Again, we see a progressive rise in cumulative RI followed by a steep decline before exit. The mean overall impact of each full episode is marginally negative; the drop from the peak to exit is drastic at 7.22 basis points (bps) of RI.

## EXHIBIT 9

### Results of Each Mixed-Effect Model

| | | | *p* Value | |
|---|---|---|---|---|
| Predicted Variable | Marginal $R^2$ | Conditional $R^2$ | Quadratic Term | Linear Term |
| Cumulative ROI | 0.06 | 0.94 | <0.001 | <0.001 |
| Cumulative RI | 0.02 | 0.73 | <0.001 | <0.001 |

**NOTE:** *p* values refer to the significance of incorporating percentage through episode within the model.

where $y$ represents the measure to be predicted, x represents episode percentage, and $\varepsilon$ represents the amount of error within the model. Both models allow the coefficients $b$ and $c$ to vary by portfolio. By taking this approach, we allow the model to capture all of the subtype trends other than the linear accumulator.

### Validation

Both ROI and RI models are able to account for a large amount of the variance within the data (Exhibit 9). To assess the significance of these findings, *p* values for the fixed effect of percentage through episode are computed using Wald's tests.

The models fitted to cumulative relative ROI and cumulative RI possess *a* coefficients of –8.89 and –0.26, respectively, indicating that the model finds that concave, rather than convex, polynomials better fit the data set as a whole.

The results of our initial analyses are highly significant, suggesting that each model could account for variance in each measure. Although the variance accounted for by the fixed effects could be considered low, several reasons could explain why this may be the case. First, behavioral data intrinsically tend to have a lower variance accounted for by fixed effects. This tendency is compounded by the sheer variability within the stock market. Second, we enter all suitable data into this analysis, despite some portfolios likely better reflecting alternative functions when compared to the one we choose here. Third, a quadratic function assumes symmetry around its maximum, which is unlikely in this data set.

## DISCUSSION

Understanding the causes of trends in alpha is highly valuable. This value is highlighted by an attempt to utilize alpha predictors to create profit-maximizing algorithms (Passerini and Vazquez 2015). Recently, a major focus of finance research has been the study of behavioral biases and subsequent irrational decision-making, which in turn impact alpha. Thaler (1999) predicts that in the future, behavioral factors will be incorporated into economists' models by default. In fact, the capital asset pricing model (CAPM) has already been improved by using behavioral factors (Rocciolo, Gheno, and Brooks 2018). These findings suggest that behavioral biases are highly relevant when trying to understand the drivers of trends in alpha.

Demonstrating the specific behavioral biases producing the alpha life-cycle effects that we observe is beyond the scope of this research, but we believe that the endowment effect (Thaler 1980) could be at play. This effect is defined as a tendency to place greater value on something for which ownership is perceived. The bias is often considered as a manifestation of loss aversion (Morewedge and Giblin 2015), a component predicted by prospect theory (Kahneman and Tversky 2013). The effect is observed among investors in experimental settings (Kalunda and Mbaluka 2012) and in retroactive analysis of the Australian stock exchange (Furche and Johnstone 2006). Query theory (Johnson, Häubl, and Keinan 2007) aims to explain the effect, proposing that sellers will place greater focus and value on positive, rather than negative, attributes of a good. When investigating this factor, researchers find that those who are considering selling a pen report more positive evaluations of the good than potential buyers (Nayakankuppam and Mishra 2005). Therefore, the effect may be partially driven by an increased saliency of positive attributions.

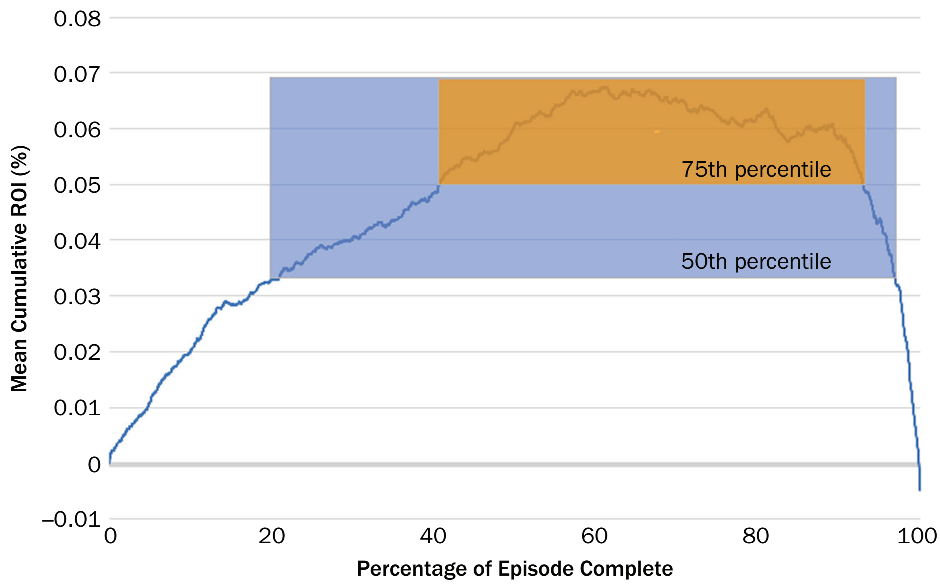
The prominent trends in cumulative relative ROI observed here can be explained in the context of these theories. That is, as an investor holds an appreciating stock, the investor imbues that stock with positive attributes. Once the stock appreciation begins to deteriorate or plateau and the investor is considering a sell, a higher value is given to longstanding positive views of the stock, leading the investor to hold the security while clearly sacrificing previous positive contributions to alpha. This account has similarities with the informal notion of *stock love*, which refers to investors holding losing stocks that were profitable in the past. Importantly, three of the four subtypes identified in our analysis exhibit a period of appreciation followed by a period of either depreciation or no further appreciation when the security is held rather than sold, mimicking this narrative. This result supports the notion that the endowment effect may be a causal factor in these trends.

### Window of Opportunity

We cannot help but state the elephant-in-the-room takeaway of this research for investment managers: the position-level alpha drop from peak to exit within each episode is dramatic—and it is well worth the effort to try to avoid it. The 7.22 bps of portfolio impact *per episode* is a significant opportunity cost for a portfolio to carry;

**EXHIBIT 10**

**Significant Window of Opportunity to Consider Exiting**




**NOTE:** The alpha life cycle for a typical position shows a 9-month window of opportunity for meaningful alpha generation.

managers who are able to close episodes at (or closer to) the top of their alpha curve can significantly reduce this overhead and improve performance.

Indeed, the aggregate alpha curve's pronounced concavity enables us to illuminate the practical benefits of selling at or near peak alpha. As mentioned previously, the average entry-to-exit episode in our study is just under a year (257 business days). The curve is in its top quartile for 133 days (about 6 months) and above 50% for about 9 months (Exhibit 10). This outcome implies a significant window of opportunity for managers to act while their positions are still producing alpha in excess of their fees.

This simple exercise leads to an important conclusion: the managers in our universe, on average, would have significantly outperformed their respective indexes *net of fees* if they had taken action to exit their positions in the top half of their alpha curve.

Stated more broadly: active managers are, in fact, generating alpha well in excess of their fees; they just need to not miss the exit window at or near the top of their alpha curve—a curve that can be calculated and charted portfolio by portfolio.

## CONCLUSION

We investigate the hypothesis that alpha accumulation within episodes has a life cycle that can be observed at a portfolio level. We make this assessment under the assumption that different investors may exhibit different behavioral biases and strategies, causing variations in this life cycle.

Our findings support these views. Grand mean plots of both cumulative relative ROI and cumulative RI suggest a predominant trend of an inverted horseshoe shape over time. At the portfolio level, the cumulative relative ROI plots suggest the presence of four alpha life-cycle subtypes. Two of these subtypes, the hopeless romantic and the coaster, resemble partial versions of a third subtype, the round tripper, and could reflect variations in investor entry and exit styles. Further investigation is warranted to gain a deeper understanding of these subtypes.

Our analysis leads us to believe that these trends are manifestations of the endowment effect. Investors frequently ascribe extra value to stocks they own simply because they own the stocks, and they thus hold on to such stocks longer than they should.

Whatever the cause, investors should be aware of the vast amounts of alpha that are being lost to poor exit timing and should take steps to identify and reconsider positions that are past their prime in terms of alpha accumulation.

The long period of relative outperformance demonstrates the possibility of escaping the steep drop in position-level alpha that defines the latter stage of most portfolio episodes. Given our work in plotting position-level alpha and demonstrating its tendency to decay over time, we are hopeful that more investors will be mindful of their own alpha life cycle, exiting positions closer to the peak of their alpha curve rather than the trough and capturing the value-added returns that are too commonly lost to the effects of biases and poor decision-making processes.

## APPENDIX A

For this study, we analyzed **detailed trade data from 2005–2019 in the following 43 equity portfolios of clients of Essentia Analytics** (identifying details of the funds are omitted).

| Emerging Markets | Europe | Global | North America |
|---|---|---|---|
| 1 Emerging Markets | 5 European all cap | 11 Global growth | 35 North American all cap |
| 2 Emerging Markets | 6 European all cap | 12 Global all cap | 36 North American all cap |
| 3 Emerging Markets all cap | 7 European all cap | 13 Global all cap | 37 North American all cap |
| 4 Emerging Markets small cap | 8 European all cap | 14 Global all cap | 38 North American all cap |
| | 9 European all cap income | 15 Global all cap | 39 North American all cap |
| | 10 European large cap | 16 Global all cap | 40 North American all cap |
| | | 17 Global all cap growth | 41 North American large cap |
| | | 18 Global all cap growth | 42 North American large cap income |
| | | 19 Global all cap growth | 43 US small cap |
| | | 20 Global all cap growth | |
| | | 21 Global all cap growth | |
| | | 22 Global large cap | |
| | | 23 Global large cap | |
| | | 24 Global large cap | |
| | | 25 Global large cap growth | |
| | | 26 Global large cap growth | |
| | | 27 Global large cap growth | |
| | | 28 Global large cap income | |
| | | 29 Global mid cap growth | |
| | | 30 Global small cap | |
| | | 31 Global small cap | |
| | | 32 Global small cap growth | |
| | | 33 Global small cap value | |
| | | 34 Global small cap value | |

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