NORTHERN TRUST

ASSET MANAGEMENT

RESEARCH REPORT

INVESTING IN VALUE WITHOUT BETTING AGAINST GROWTH

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KEY FINDINGS

- We leverage machine learning techniques (clustering) to group stocks based on growth characteristics, allowing the number of clusters to vary over time.
- We present a simple case study which forms a relative value portfolio by ranking and sorting stocks within each growth cluster.
- The results show that it may be possible to fully capture the value premium while reducing the sensitivity to the value/growth cycle.

SUMMARY

Value and growth are often considered to be mutually exclusive, forcing investors to choose between one or the other. Since the dot-com era, value investing has become synonymous with long cycles and extreme returns. In this paper we explore an approach to value investing that conditions on growth, aligning it with the concept of intrinsic value. We apply a form of unsupervised learning to group stocks based on growth characteristics and allow it to adapt the number of clusters to the current economic regime. We present a case study which demonstrates how this technique mitigates the anti-growth bias commonly embedded in value strategies while maintaining a strong value orientation. We believe such an approach may allow investors to capture the value premium while attenuating the length and depth of drawdowns.

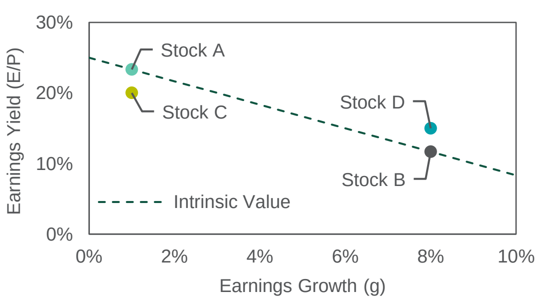
Value and growth have long been portrayed at opposite ends of the investment universe. This convention is firmly established in allocation models and index methodologies which map stocks (portfolios) along a single value/growth spectrum. In this context, the relationship between value and growth is akin to price and yield in the bond market – when one goes up, the other must go down, requiring investors to choose between the two. While value has rebounded nicely in recent years, many investors are concerned whether the easing of inflation and subdued economic outlook are signaling the dawn of another protracted period of accommodative policy. Such conditions may increase the premium for future earnings potential, tilting the balance of favor back towards growth. Is the choice between value and growth really a zero-sum game? Through the lens of intrinsic value, both are inseparable parts of a stock's valuation. In this paper, we utilize unsupervised learning to align traditional value signals with fundamental growth metrics in a manner that adapts to the macro environment. With this approach, we find it is possible to capture the value premium over the long run while neutralizing the anti-growth bias inherent in most value strategies.

INTRINSIC VALUE

The success of any value strategy is predicated on identifying under-valued stocks (over-valued stocks), which revert towards their fair market price over a given holding period. While there is no universally accepted value definition, many of them employ one or more accounting metrics such as sales, earnings, and cash flows. While current metrics are often used (e.g., trailing twelve-month earnings), any textbook will show that a stock's valuation needs to consider both current and future fundamentals, i.e., future growth.

To illustrate the concept, **Exhibit 1** evaluates four hypothetical stocks using a one-stage Gordon Growth Model (Eq. [1]), in which each stock has the same dividend payout ratio (p) and average cost of capital (r). The intrinsic value line represents the fair price (earnings yield) for each stock as a function of its earnings growth rate. In this example, Stocks A and B both reside on the intrinsic value line, and are thus fairly priced. Stock C is expensive, as it trades at a lower earnings yield than its earnings

Exhibit 1: Intrinsic Value (Gordon Growth Model)



$$P = \frac{E \times p}{r - g} \qquad \text{Eq. [1]}$$

Where:

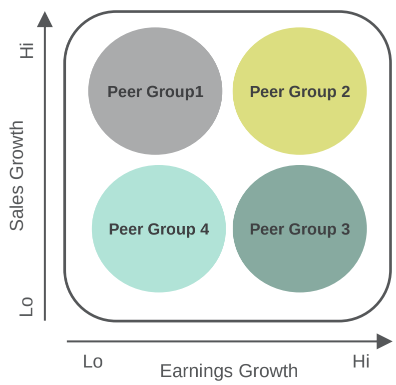
P is stock price;
E is current earning per share;
p is dividend payout ratio;
r is average cost of capital;
g is earnings growth rate;

growth warrants. Stock D is the only stock among the four that is under-valued, despite having a lower earnings yield than both Stock A and Stock C. This simple example illustrates the need to evaluate value in the context of growth. A value strategy that relies solely on current earnings yield will likely include the expensive stock (Stock C), while excluding the cheap one (Stock D). Of course, as most practitioners know, forecasting future growth rates is far from trivial.

FINDING VALUE WITHIN GROWTH

One of the biggest challenges in determining a stock's intrinsic value is projecting future earnings. Accurate forecasts require both "top-down" (e.g. economic growth, consumer preferences, industry innovation, etc.) and "bottom-up" foresight (e.g. evaluating a company's strategy and its ability to execute). To complicate matters further, many academic studies[1] suggest these estimates are subject to behavioral biases. Given the difficulty of this task, investors may choose to focus instead on identifying peer groups with similar growth potential. **Exhibit 2** presents a conceptual model whereby peer groups are identified in two dimensions – sales growth and earnings growth. We note that such a model need not be limited to two dimensions, and may include historical growth rates as well as future projections. Once peer groups are identified, relative value portfollios may be formed within each group and aggregated to form a single value portfolio. The resulting portfolio is designed to capture the value premium while neutralizing the negative growth bias that commonly accompanies value strategies.

Exhibit 2: The Conceptual Model



While the conceptual model put forth is relatively straightforward, a number of questions arise. How should the boundaries be defined? Given the direct linkage between sales growth and earnings growth, will Peer Groups 1 & 3 be sparsely populated? Are four peer groups sufficient, or should we form more (or less)? Should the number of groups (and their boundaries) respond to changing market environments? To address these questions we apply a form of unsupervised learning known as clustering.

Exhibit 3 identifies four sample "growth clusters" after applying the K-means clustering[2] algorithm on all stocks in the MSCI World Index as of December 31, 2022. The K-means algorithm[3] forms "k" groups of data such that the sum of squared distance from each data point to its cluster's center (the Centroid) is minimized. In order to provide equal emphasis to (historical) sales growth[4] and (historical) earnings growth, both variables have been winsorized[5] and standardized prior to running the algorithm – a practice known as "feature scaling." The distance formula in this example is given in Equation 2:

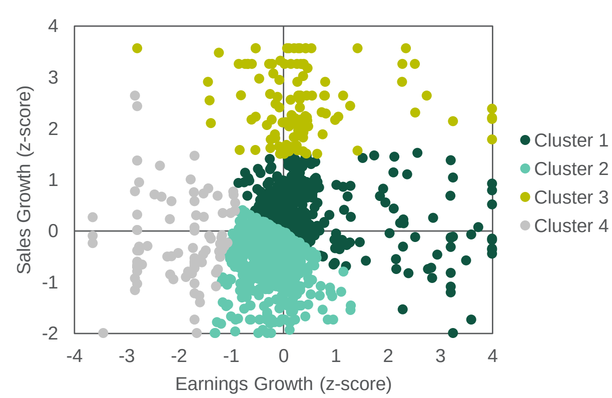
$$D_i = \sqrt{(epsG_i - epsC_i)^2 + (spsG_i - spsC_i)^2} \qquad \text{Eq. [2]}$$

Where:

- $epsG_i$ = Earnings per share growth rate (z-score) of stock i;
- $epsC_i$ = Earnings per share growth rate (z-score) of stock i's cluster Centroid;
- $spsG_i$ = Sales per share growth rate (z-score) of stock i;
- $spsC_i$ = Sales per share growth rate (z-score) of stock i's cluster Centroid;

Smaller distance between a pair of stocks implies similarity in terms of growth rates. Therefore, the goal of the clustering algorithm in this context is to form groups with the most similar growth characteristics. When comparing the results of Exhibit 3 to the conceptual model (Exhibit 2), we see a stark contrast in the orientation among the groups. This implies that forming groups by quadrants, though conceptully appealing, is suboptimal.

Exhibit 3: Growth Clusters in the MSCI World Index, k=4 (12/31/2022)

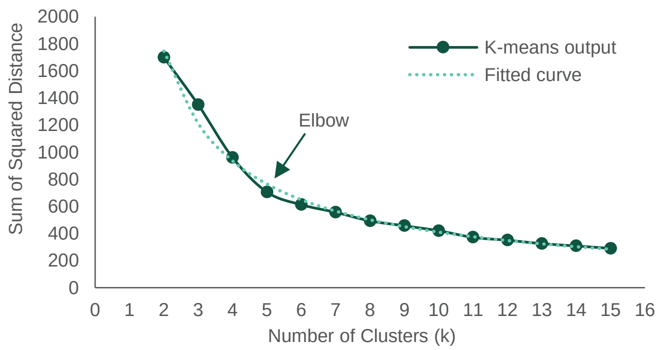


Source: Northern Trust Quantitative Research, MSCI, FactSet. Data as of 12/31/2022

[1] Lakonishok, Shleifer and Vishny (1994) showed that growth rate forecasts of glamour stocks were often too optimistic compared to value stocks; Kahneman and Riepe (1998) made similar arguments that investors overpaid for growth stocks due to their over confidence in projecting high earnings growth.
[2] K-means clustering is widely used and therefore chosen for illustrative purposes.
[3] For additional information refer to the Appendix.
[4] Quarterly sales (earnings) per share are regressed against time over the past three years. The slope coefficient is then divided by the average quarterly sales (earnings) per share.
[5] Features were winsorized at the 2.5% and 97.5% levels.

The number of clusters (k) chosen as input are highly influential in determining the clustering algorithm's output. While increasing the number of growth clusters may reduce the anti-growth bias, too many peer groups may make the grouping fragmented and ultimately less effective. Although heuristics may be employed, methodologies exist to help inform this decision. One technique known as the "Elbow method" is depicted in **Exhibit 4**. The Elbow method[6] first generates the "Elbow curve" by running the clustering algorithm over a range of clusters (2 through 15 in this example) and capturing the sum of squared distances at each iteration. It then identifies the value of "k" where the curvature is maximized. We can see from these results that the Elbow method selects k=5 for the MSCI World Index as of 12/31/2022.

Exhibit 4: Clustering Elbow Curve MSCI World Index (12/31/2022)

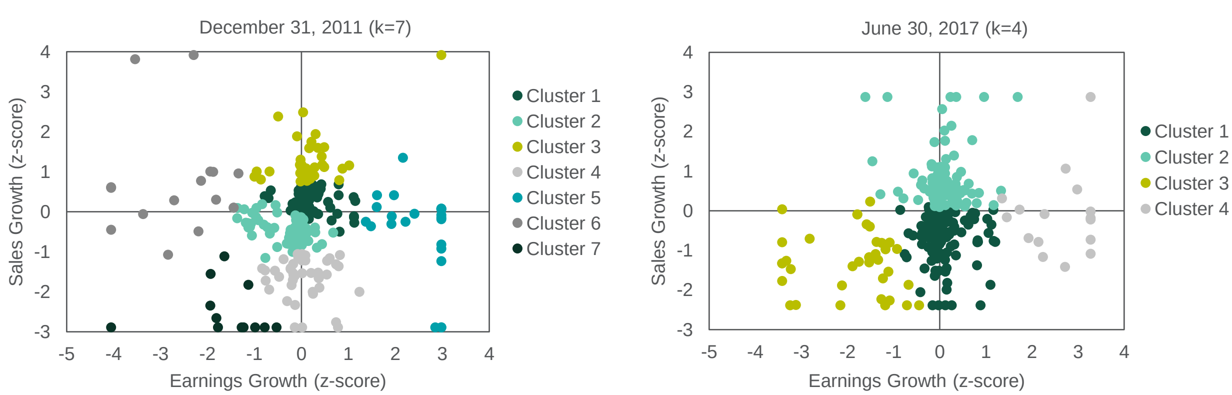


Source: Northern Trust Quantitative Research, MSCI, FactSet. Data as of 12/31/2022.

When we combine a clustering algorithm with a method to determine the appropriate number of clusters, we have the ability to adapt to changing market environments. In order to test this, we extended our analysis from December 1999 through December 2022 in the MSCI World Index, and applied feature scaling by region: Europe, Japan, North America, Pacific, and the UK. We applied K-means clustering within each region at every quarter end, and captured the resulting Elbow method output. Over the 23-year period, the minimum and maximum number of clusters for each region (min,max) supports our hypothesis that the output is time-varying: Europe (3,7), Japan (3,8), North America (4,7), Pacific (2,7), and the UK (3,8).

An example of this variation is highlighted in **Exhibit 5**, which plots two distinct time periods for the European region. When comparing the scatterplots, we see much more dispersion in the chart on the left (k=7) as compared to the chart on the right (k=4). Although both time periods have been winsorized at the same level, the range of z-scores in December 2011 is wider for both sales growth and earnings growth. In addition, each of the four quadrants are more evenly populated in December 2011 than June 2017, particularly the upper left quadrant (low earnings growth and high sales growth).

Exhibit 5: Growth Clusters in the MSCI World Index, European Region



Source: Northern Trust Quantitative Research, MSCI, FactSet. Data as of 12/31/2011 and 6/30/2017.

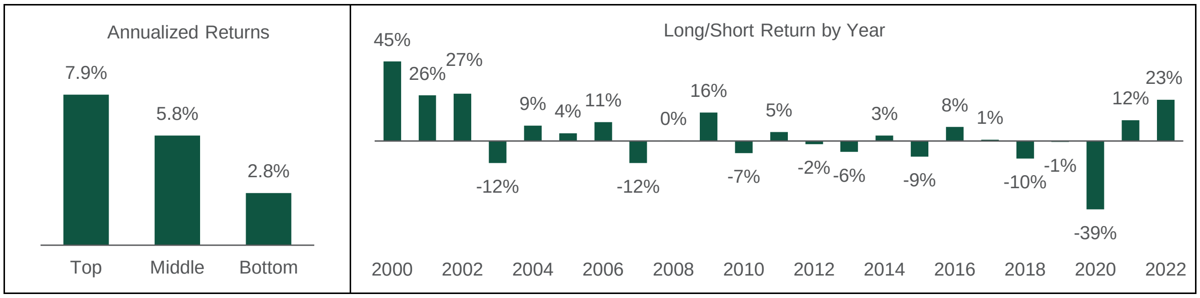
MITIGATING THE ANTI-GROWTH BIAS

In order to gauge the impact of growth clustering to value investors, we evaluated a simple case study from the perspective of an earnings yield[7] investor. For the purpose of our analysis, we first created a baseline by ranking and sorting constituents by earnings yield within each region[8] of the MSCI World Index, and bucketing all stocks into three groups[9]: Top (30%), Middle (40%), and Bottom (30%). Portfolios were formed by weighting all stocks within each group by

[6] We refer here to the "Elbow method" generally as there is more than one implementation (both numerical and analytical). In all cases the method attempts to locate the value of "k" that has the maximum curvature.
[7] P/E ratios are arguably the most commonly cited valuation multiple, and therefore selected for this example.
[8] Regions are defined as before: Europe, Japan, North America, Pacific, and the UK.
[9] We follow ranking and sorting methodology established in the classic factor literature.

their respective market capitalization at each quarter end (i.e. rebalanced quarterly). **Exhibit 6** summarizes the performance of earnings yield using this methodology from December 31, 1999 through December 31, 2022.

Exhibit 6: Performance of Earnings Yield (E/P) in the MSCI World Index (12/31/1999 – 12/31/2022)



Source: Northern Trust Quantitative Research, MSCI, FactSet. Data from 12/31/1999 to 12/31/2022. Top (30%), Middle (40%) and Bottom (30%) portfolios were formed by earnings yield, market-cap weighted, and rebalanced quarterly.

The annualized returns reported in the chart on the left are consistent with the value premium documented extensively in the factor literature. Over the 23-year period ending December 31, 2022, the top earnings yield portfolio outperformed the bottom portfolio by over 5% (7.9% vs. 2.8%). Unfortunately, the long/short returns (Top minus Bottom) shown on the right reveal that much of this performance was attributed to the early 2000's when the euphoria of the "tech bubble" burst. In fact, the value premium disappears almost entirely in this example if the first three years[10] are excluded. However, the same argument can be made in the other direction, as value's collapse in 2020 was entirely responsible for eliminating the value premium over the past 20 years. If one were to remove that year, the value premium again appears robust. Of course, this is not the reality for investors. While long-term value investors must be willing to accept some exposure to the value/growth cycle, many of them would gladly forego the extremes if it were possible to preserve the mean.

To determine whether growth clustering may be useful towards this goal, we extended our baseline earnings yield example with one modification – by ranking and sorting stocks within each region and cluster. Portfolios were then formed exactly as before, bucketed into Top (30%), Middle (40%) and Bottom (30%) portfolios. **Exhibit 7** plots the rolling three year[11] difference in active return between the top "growth cluster" earnings yield portfolio and that of the baseline. We find the results to be both encouraging and intuitive, as the spectacular performance of value in the early 2000's was sacrificed in order to bolster performance when value lagged. Over the time period analyzed, the trailing three-year active return difference was positive 83% of the time (201 of the 241 months reported). Though we present these results from the perspective of the long-only investor, we see a similar pattern when comparing long/short returns (refer to Exhibit B in the Appendix).

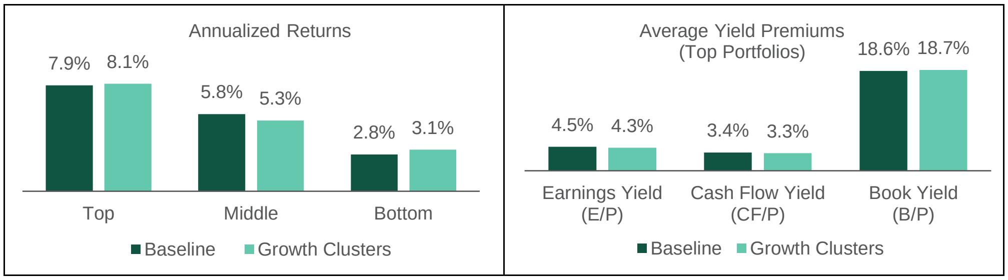
Exhibit 7: Rolling Three-Year Active Return Difference in Earnings Yield Portfolios (Top 30%) Growth Clusters vs. Baseline, MSCI World Index (12/31/1999 – 12/31/2022)

Source: Northern Trust Quantitative Research, MSCI, FactSet. Data from 12/31/1999 to 12/31/2022. Top (30%) portfolios were formed by earnings yield, market-cap weighted, and rebalanced quarterly.

We conclude our analysis in **Exhibit 8** by comparing the performance and value profile[12] of the two methodologies, where "Yield Premiums" are reported for the Top (30%) portfolios in excess of the market. For example, the earnings yield premium is computed by averaging the difference between the earnings yield of the Top (30%) portfolio and the earnings yield of MSCI World Index at every month end.

[10] Over the 20 year period ending December 31, 2022 the annualized return spread (Top vs. Bottom) is only 0.1% (8.8% vs. 8.7%).
[11] Three years represents a common evaluation period for active strategies.
[12] In the case of Cash Flow Yield (CF/P), Financials and Real Estate are excluded.

Exhibit 8: Comparison of Earnings Yield Portfolios in the MSCI World Index (12/31/1999 – 12/31/2022)



Source: Northern Trust Quantitative Research, MSCI, FactSet. Data from 12/31/1999 to 12/31/2022. Top (30%), Middle (40%) and Bottom (30%) portfolios were formed by earnings yield, market-cap weighted, and rebalanced quarterly.

Although the difference in active returns reported in Exhibit 7 is significant (range of +/- 2%), the full period performance of the respective portfolios shown in Exhibit 8 are quite similar. The top growth cluster portfolio outperformed the baseline by 20 bps (8.1% vs. 7.9%), but the Top vs. Bottom return spread compressed 10 bps (5.0% vs. 5.1%). Interestingly, the average yield premiums indicate that the value content of the top baseline portfolio has been largely preserved – the earnings and cash flow yields of the top growth cluster portfolio are slightly lower than the baseline, while the book yield is slightly higher.

CONCLUSION

Value and growth are often considered to be mutually exclusive, forcing investors to choose between one or the other. Since the dot-com era, value investing has become synonymous with long cycles and extreme returns. In this paper we explored an approach to value investing that conditions on growth, aligning it with the concept of intrinsic value. By leveraging clustering, we grouped stocks based on the similarity of their growth characteristics and allowed the algorithm to adapt the number of clusters to the current economic regime. The case study demonstrated how these techniques may be used to mitigate the anti-growth bias commonly embedded in value strategies while maintaining a strong value orientation. We believe such an approach may allow investors to capture the value premium while attenuating the length and depth of drawdowns, ultimately making it easier for value investors to stay the course.

APPENDIX

Methodology Notes

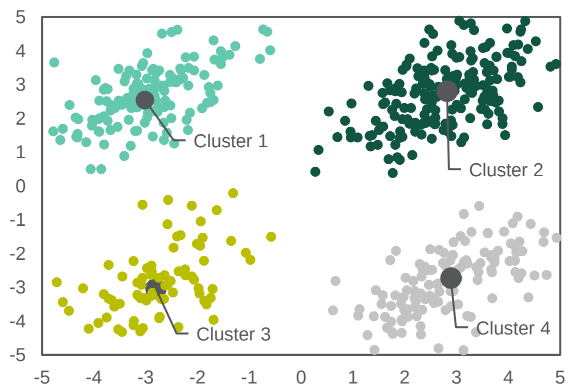
K-Means Clustering

K-means clustering is an unsupervised machine learning algorithm which classifies unlabeled feature data sets into mutually exclusive groups (clusters), where "k" represents the total number of data clusters. The clustering algorithm identifies center points (Centroids) for each group and assigns observations to clusters such that the total distance of all data points to the Centroids are minimized. Equation 3 shows the utility function of the clustering algorithm. Exhibit A shows an example of K-means clustering output.

$$min \sum_{i=1}^{k} \sum_{x \in S_i} ||x - C_i||^2 \qquad \text{Eq. [3]}$$

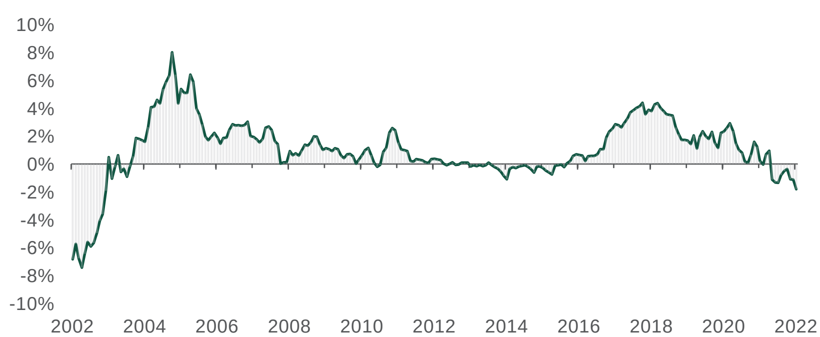
Where k = total number of clusters;
C_i = Centroid of the i_{th} cluster;
x = feature data set belonging to the i_{th} cluster;
$||x - C_i||^2$ = Euclidean distance between the feature data set and Centroid;

Exhibit A: Sample K-Means Clustering Output



Supplemental Exhibits

Exhibit B: Rolling Three-Year Long/Short Return Difference in Earnings Yield Portfolios (Top 30%) Growth Clusters vs. Baseline, MSCI World Index (12/31/1999 – 12/31/2022)



Source: Northern Trust Quantitative Research, MSCI, FactSet. Data from 12/31/1999 to 12/31/2022. Top (30%), Middle (40%) and Bottom (30%) portfolios were formed by earnings yield, market-cap weighted, and rebalanced quarterly.

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