**Study of Individual Time Series of 20,000+ Valuentum Buying Ratings**

# Value and Momentum Within Stocks, Too

An Introduction to the Valuentum, the Value-Timing and the Ultra-Momentum Factors

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**Abstract**

This paper strives to advance the field of finance in four ways: 1) it extends the theory of the "The Arithmetic of Active Management" to the investor level; 2) it addresses certain data problems of factor-based methods, namely with respect to value and book-to-market ratios, while introducing price-to-fair-value ratios in a factor-based approach; 3) it may lay the foundation for academic literature regarding the Valuentum, the value-timing, and ultra-momentum factors; and 4) it walks through the potential relative outperformance that may be harvested at the intersection of relevant, unique and compensated factors within individual stocks.



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## I. Introduction

*The Valuentum Buying Index*

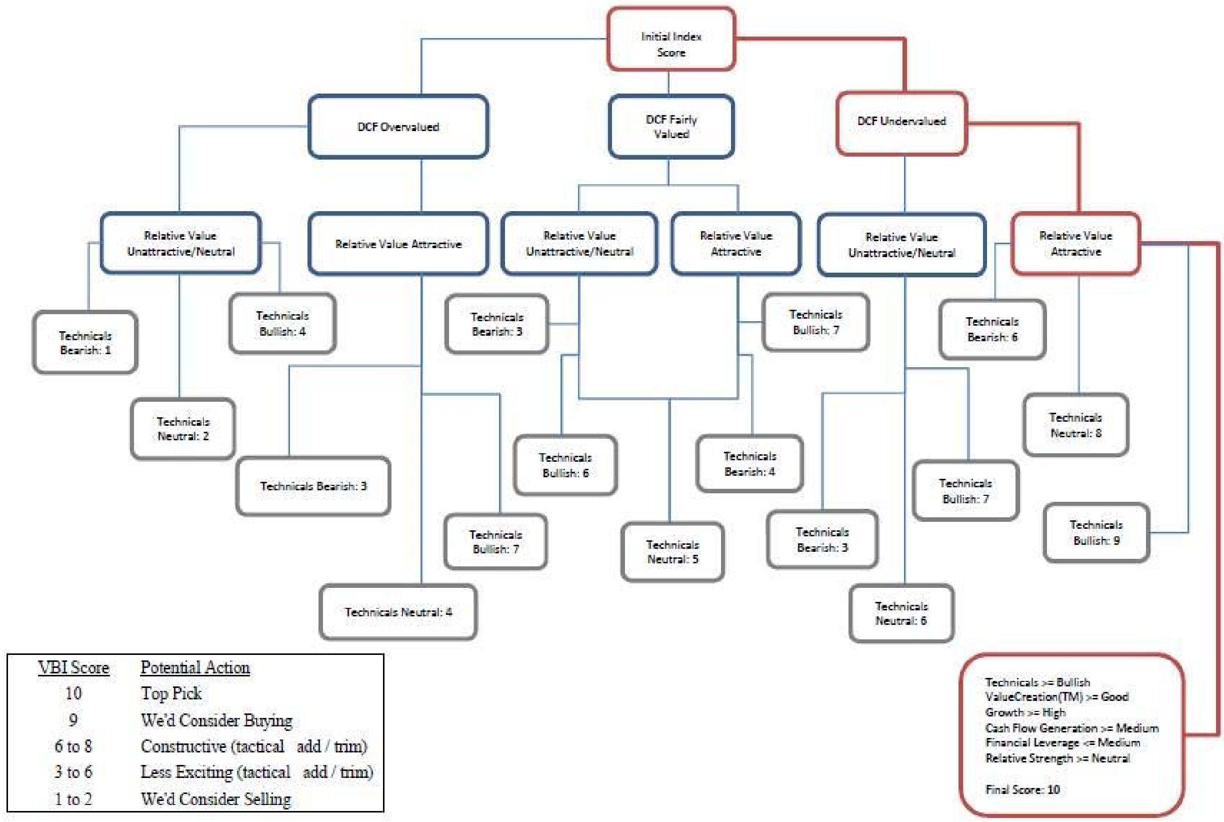
The Valuentum Buying Index is a fundamentally-based and forward-looking stock-selection methodology that captures an assessment of the value and technical/momentum qualities *within individual stocks* at particular points in time. The Valuentum Buying Index combines company valuation analysis with an evaluation of a stock's technical/momentum indicators to derive a single rating between 1 and 10 for each company at each point of measurement (10=best; 1=worst). A Valuentum Buying Index rating is generated via a three-step process.

First, the Valuentum Buying Index makes use of a forward-looking enterprise free cash flow model (DCF), enhanced by a fair value range or margin of safety, to determine whether we think a stock is overvalued, fairly valued, or undervalued on a DCF basis. Second, a stock's forward price-to-earnings ratio and forward price-earnings-to-growth ratio are assessed to determine whether a stock is unattractive, neutral, or attractive versus peers on a relative value basis. Third, a stock's technical/momentum indicators are assessed to determine whether such indicators are bearish (poor), neutral, or bullish (good).

Depending on how each stock performs with respect to each component (DCF value, relative value, technical/momentum indicators) and based on the order-of-process as defined by the flow chart in Figure 1, a Valuentum Buying Index rating is assigned to a stock at particular points in time. Though qualitative and subjective considerations are embedded into the process (fair value estimates, for example, are derived by analysts), each Valuentum Buying Index rating is systematically generated. The Valuentum Buying Index, however, is differentiated from quantitative multi-factor models that may employ various historical value, momentum and timing dynamics.

In this paper, we study the nature of future returns of Valuentum Buying Index ratings in two ways. First, to assess the performance of Valuentum Buying Index ratings in identical market conditions, we examine the performance of a cohort of randomly-selected Valuentum Buying Index ratings from one distinct point in time to another ("Case Study"). Second, to assess timing considerations regardless of market conditions, we assess the future returns of 20,000+ Valuentum Buying Index ratings on stocks on the basis of their individual time series ("Time Series Study").

**Figure 1: Process Deriving Valuentum Buying Index Ratings**




*Notes:* This figure showcases the process by which factors within stocks are sorted among Valuentum's stock coverage universe. For example, a stock that registers a 1 on the Valuentum Buying Index is estimated to be overvalued on the basis of an enterprise free cash flow process (i.e. its share price trades above the upper bound of a fair value estimate range), unattractive or neutral on a relative value basis, and have bearish technical/momentum indicators. On the other hand, a stock that registers a 10 on the Valuentum Buying Index is estimated to be undervalued on the basis of an enterprise free cash flow process (i.e. its share price trades below the lower bound of a fair value estimate range), attractive on a relative value basis, and have bullish technical/momentum indicators, as well as possess a number of other theoretical compensated factors, including quality (a good ValueCreation rating) and possibly others. ValueCreation indicates the firm's historical track record in creating economic value for shareholders, taking the average difference between ROIC, without goodwill, and the firm's estimated weighted average cost of capital during the past three years. Those firms with ratings of good or higher have a demonstrated track record of creating economic value. A price-to-fair value ratio (P/FV) compares the company's share price to an enterprise free-cash-flow (DCF) derived estimate of a company's intrinsic value.

## *On factors*

At no time in the history of the stock market has so-called factor-based investing been more popular. Factor-based investing can trace its roots back to the days of Benjamin Graham's and David Dodd's text, *Security Analysis* (1934), when value investors first started to focus on the concept of value, or stocks that had attractive valuation characteristics. In Graham's and Dodd's case, it would be investing in stocks that were trading below net current asset value (NCAV), a stock-selection approach originally tested in the early 1930s, as Graham so eloquently outlined in the *Intelligent Investor* (1973).

> A good part of our own operations on Wall Street had been concentrated on the purchase of *bargain issues* easily identified as such by the fact that they were selling at less than their share in the net current assets (working capital) alone, not counting the plant account and other assets, and after deducting all liabilities ahead of the stock (Graham 2003).

In some ways, factor-based investing can be viewed as another name for style investing, and some well-documented, compensated stock factors, or those revealing "empirical evidence of historical positive risk-adjusted excess returns associated with them," can include market, value, size, momentum, quality and low volatility (Pappas, Dickson 2015). Investors that like to hold stocks with low price-to-earnings ratios, for example, may have exposure to what is called a value factor, while a momentum factor might be broadly defined as stocks with strong recent share-price performance. In another instance of well-known factor-based research, for example, Nobel laureate Eugene Fama's and Kenneth R. French's Five-Factor Asset Pricing Model builds on their original groundbreaking Three-Factor Asset Pricing Model, adding the factors of profitability (stocks with high operating profitability may have better returns) and investment (stocks with higher total asset growth may have lower returns) to the original three: market (stocks with high betas may have better returns), size (small-cap stocks may have better returns), and value (stocks with high book-to-market ratios may have better returns).

There is no comprehensive and definitive list of what is or isn't a factor, so it's important to note that there could be as many factors as there are ways to analyze a stock, some of which are compensated and some not (Pappas, Dickson 2015). The list of factors continues to grow, with now more than 600 factor-based exchange-traded funds (ETFs) on the market today, up from just 20 in 2001 (Nielsen 2016), but after decades of research and analysis, it's important to emphasize that even Fama and French's latest "five-factor model can leave lots of the cross-section of expected stock returns unexplained (Fama-French 2014)." More recently, many have even concluded that "it is crystal clear that CAPM (Capital Asset Pricing Model) and its Betas do not explain anything about expected or required returns (Fernandez 2017)." As is the case for most theoretical, behavioral sciences such as finance, where no complete or definitive answer may exist, there are many varying opinions and much still to discover:

> Debate continues on the investment rationale supporting certain factor returns. In some cases—for example, the equity market factor—a strong economic rationale exists for an excess return premium. The equity market premium has been deeply researched, and, although there is uncertainty over the future size of the premium, it is widely accepted that over the long term a positive excess return (above the "risk-free" rate) will be associated with the equity market factor. For many other factors, however, both the logic

and economics explaining potential return premiums are subject to debate (Pappas, Dickson 2015).

*Origins of Valuentum thinking*

The origins of the thinking behind the Valuentum factor, the Valuentum Buying Index, or the Valuentum Style of Investing, rest in the peculiarities of the success of fund managers and investors that have blended various strategies or factors *within individual stocks* to achieve unusual periods of fund or portfolio outperformance (Nelson 2011). For example, famed money-manager Bill Miller, formerly of Legg Mason, developed a remarkable streak of exceeding the S&P 500 Index return for 15 consecutive years starting in 1991, in part by investing in growth-oriented stocks that seemingly had a value-tilt, or by theoretically combining the factors of growth and value within individual stocks, with such stocks forming a large portion of his value fund--the Legg Mason Value Trust. During part of his streak, for example, some large holdings in the Legg Mason Value Trust--namely companies with high price-to-earnings ratios such as Amazon (AMZN), eBay (EBAY), and Google (GOOG)--may have had more characteristics of growth at the time than value, but arguably such stocks had both characteristics if their subsequent fundamental and equity price performance is any indication (CNN Money 2006).

There are other examples. Manu Daftary, president of DG Capital Management and portfolio manager of the Quaker Strategic Growth Fund exceeded the S&P 500 Index return for 8 consecutive years, ending in 2006. In Daftary's case, for example, combining other factors with traditional growth within individual stocks, as in moving into sectors in favor (momentum), namely the cyclical and commodity-driven energy sector in 2004, may have helped fuel the strength of certain "growth-oriented" energy holdings, leading to overall outperformance in the fund (Investment News 2006). At the time both Miller's and Daftary's winning streaks came to an end, there were several other funds that had seven-year winning periods, revealing such streaks of relative outperformance may not be as uncommon as popular opinion may lead one to believe. In yet perhaps the most obvious case, however, Warren Buffett's investment style, which has evolved greatly during the past several decades, may at its core be one that captures a combination of an economic-moat, or quality, factor and a value factor within individual stocks, the overlap of the two perhaps explaining a significant amount of Berkshire Hathaway's outperformance during the past several decades.

Observing the success of fund managers and investors that seemingly combined diverse styles (factors) within individual stocks--growth and value in Bill Miller's case; growth and sector momentum in Manu Daftary's case; and value within competitive-advantaged companies in Warren Buffett's--we have long hypothesized that such respective relative outperformance of the most successful investors can in part, or largely, be attributed to a phenomenon where such fund managers and investors, knowingly or unknowingly, have had large exposures to relevant, unique and compensated factors *within individual stocks*, forming unique investment styles that go commonly undefined today (i.e. styles that are outside traditional style boxes). We reason that, in stocks containing a large number of relevant, unique and compensated factors, what transpires is significant and sustained buying in such stocks by a larger number of investors for sustained periods of time, as theoretically such stocks fit the criteria of a large, diverse cross section of investment styles. This, we have believed, is the reason why such stocks (and therefore the funds that hold such stocks) may exhibit strong, sustained relative outperformance for certain--and sometimes extended--periods of time, and academic research may indirectly support this view via style-drift evaluation.

> …managers of growth-oriented funds and small funds, and managers having good stockpicking track records, tend to have higher levels of style drift than other managers; these managers also deliver better future portfolio performance as a result of their trades, even after accounting for their higher trading costs. Consistent with this superior performance, managers do not seem to be concerned with controlling style drift; indeed, managers tend to be "style chasers" during most years, which appears to benefit their performance… (Wermers 2010).

*Some observations*

First, as the number of factors continues to grow with each passing year, we have become increasingly interested in identifying which types of generally-undefined investment styles, or combination of unique factors, are responsible for such seemingly positive and sustained market-return anomalies that occur when multi-factor, cross-style methodologies within individual stocks are pursued (e.g. Miller, Daftary, Buffett, etc). As style drift has been shown to account for better future performance in portfolios, even after accounting for higher trading costs, the benefits of learning about style drift phenomena and extending that to individual equities may have considerable benefits. In its traditional definition, style drift may have negative connotations to investors that may rely on advertised styles, but studies that address cross-methodological frameworks within individual stocks may help push forward the understanding of many facets in the field of finance.

Others may be thinking similarly. Recent academic research has revealed how the track records of Warren Buffett, Bill Gross, George Soros, and Peter Lynch can be viewed as a function of a few factor-based investment styles. After controlling for the factors of value, low-risk, and quality, for example, Warren Buffett's "alpha becomes statistically insignificant (AQR 2016)." Further analysis may reveal that the best stocks within Berkshire Hathaway's portfolio may have been the ones with the greatest overlap of the factors of value, low-risk, and quality, among others; in identifying these types of stocks is where our interests are focused. Also of relevance have been interpretations of the AQR 2016 study on Peter Lynch's eclectic style: "Lynch wasn't value, he wasn't growth, he wasn't size and he wasn't quality. Instead he was all of those things at the same time (Alpha Architect 2017)." One may hypothesize that the majority of stocks that Peter Lynch held in his Magellan Fund, or the ones that contributed most to outperformance, may have had the greatest number of relevant, unique and compensated factors *within them*, a phenomenon that may have resulted in the greatest buying interest in such stocks and therefore relative outperformance of the fund.

Second, it should be clearly acknowledged that categorizing stocks as having a factor will always be an imprecise endeavor. For starters, each individual stock theoretically has an infinite number of characteristics within it--some contradicting--and such characteristics, namely growth or value as examples, cannot, in our view, be authoritatively defined. Stocks with low price-to-earnings ratios and/or high book-to-market ratios (traditional "value' stocks) can be expensive on the basis of traditional enterprise valuation processes, while stocks with high revenue and earnings growth (traditional "growth' stocks) can be undervalued on the basis of other value measures. As a result, we view attempts to assign benchmarks to certain funds or portfolios as somewhat arbitrary, as the endeavor remains a highly discretionary practice. Commonly-used stock categorizations such as value and growth may be most limiting, and we are reminded every day of the interaction of factors within individual stocks in the context of an enterprise free cash flow model (i.e. growth will always be a component of value).

> But how, you will ask, does one decide what's "attractive"? In answering this question, most analysts feel they must choose between two approaches customarily thought to be in opposition: "value" and "growth." Indeed, many investment professionals see any mixing of the two terms as a form of intellectual cross-dressing.
>
> We view that as fuzzy thinking (in which, it must be confessed, I myself engaged some years ago). In our opinion, the two approaches are joined at the hip: Growth is always a component in the calculation of value, constituting a variable whose importance can range from negligible to enormous and whose impact can be negative as well as positive.
>
> In addition, we think the very term "value investing" is redundant. What is "investing" if it is not the act of seeking value at least sufficient to justify the amount paid? Consciously paying more for a stock than its calculated value - in the hope that it can soon be sold for a still-higher price - should be labeled speculation (which is neither illegal, immoral nor - in our view - financially fattening) -- (Buffett 1992).

Third, the luck-versus-skill question in evaluating abnormally-strong portfolio returns may not be as important as identifying and understanding criteria within the underlying stocks that have driven such abnormally-strong portfolio returns. It may be much less controversial, for example, to believe that both growth and value investors may be interested in the same kinds of stocks that have overlapping characteristics of both good growth and good value (e.g. Bill Miller), and similarly that economic-moat and value investors may be interested in the same kinds of stocks that have overlapping characteristics of both wide moats and good value (e.g. Warren Buffett), and that this may be the reason for relative outperformance than it is in saying such multiple streaks of consecutive annual years of relative fund outperformance are a matter of skill--even as studies suggest that for many great investors, success for them "is not luck or chance (AQR 2016)."

Building off the commentary in Mauboussin 2013, in baseball terms, the question may instead be more about how many players *would have hit* .400 in Major League Baseball since Ted Williams exceeded such a mark in 1941, or how much better league averages might be, if all that was measured in such a batting average were the swings on pitches in "sweet spots"--or in finance terms, if investment managers focused solely on the intersection of the most relevant, unique and compensated factors within individual stocks. As more and more data in the game of baseball is being collected, we now can measure statistics such as exit velocity and launch angles on homerun swings, perceived speeds and spin rates on four-seam fast balls (Statcast 2017), and soon we may even be able to measure batting averages, adjusted for swings through a hitter's sweet spot. Such data, for example, has already influenced the launch angles of many hitters' swings, resulting in more homeruns in the game of baseball than ever before (Sheinin 2017).

*Extending the body of work behind the arithmetic of active management*

It was 1973, and a Princeton economist by the name of Burton G. Malkiel had just published *A Random Walk Down Wall Street*, a book that would turn into one of the most influential studies in support of the efficient markets hypothesis, a financial theory originally developed by Eugene Fama that generally states it is impossible to beat the market on a risk-adjusted basis, that stocks always trade at their fair value, and that stock selection and market timing are generally fruitless endeavors (Fama 1965). Malkiel's book would suggest that asset prices typically exhibit signs of a "random walk," and as a result, an investor could not consistently outperform market averages in part due to powerful reversion-to-the-mean tendencies: "…the market prices stocks so efficiently that a blindfolded chimpanzee throwing darts at the Wall Street Journal can select a portfolio that performs as well as those managed by the experts (Malkiel 2003)." Others have subsequently hypothesized that monkeys might even do better than the experts (Ferri 2012).

A couple years following the original publishing of Malkiel's masterpiece, the book's popularity would offer a backbone for the launch of the first "passive" index fund, and the ideas within it would serve as the foundation for indexers far and wide for decades. As of the end of 2016, more than 420 index mutual funds manage a collective sum of \$2.6 trillion, with nearly \$200 billion of net new cash flow added to index mutual funds in 2016 alone, a measure that has gradually increased in each of the previous three years and one that is significantly higher than the 2007-2012 average of ~\$60 billion. Index equity mutual funds' share of total net assets has swelled to nearly 25% by the end of 2016 from under 10% in 2001 (Reid 2017). Some have even estimated that "the proportion of stocks on the main US benchmark index (S&P 500) now managed passively has nearly doubled since the 2008 crisis to 37% (CNBC 2017)."

A discussion of the systemic risk that may arise from a growing percentage of investors pursuing passive products (and quantitative investors modeling on such behavior) may be beyond the scope of this paper, but as any discussion of the potential presence of factor-based relative outperformance might, especially ones considering controversial value-timing and ultra-momentum factors, we must address the elephant in the room--the arithmetic of active management. For background, academia and much of popular finance has generally operated under the following arithmetic assumptions, with variations of such syllogisms being reproduced during the past several decades in many forms and formats, often cited in works of great quality far and wide.

> If "active" and "passive" management styles are defined in sensible ways, it must be the case that
>
> (1) before costs, the return on the average actively managed dollar will equal the return on the average passively managed dollar and
>
> (2) after costs, the return on the average actively managed dollar will be less than the return on the average passively managed dollar. (Sharpe 1991)
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> ----------
>
> 1. All investors own the entire stock market, so both active investors (as a group) and passive investors—holding all stocks at all times—must match the gross return of the stock market.
>
> 2. The management fees and transaction costs incurred by active investors in the aggregate are substantially higher than those incurred by passive investors.
>
> 3. Therefore, because active and passive investments together must, by definition, earn equal gross returns, passive investors must earn the higher net return. QED. (Bogle 1999)

It's perhaps not obvious, but also consistent with such syllogisms that some investors can and do outperform a market benchmark (index), and some consistently so. The syllogisms above, which fall short of describing the market from the perspective of the investor, assess outcomes in terms of dollars and aggregates, respectively, instead of averages. For illustrative purposes, and to show the hazards that may materialize from oversimplified generalizations of the stock market, we show by hypothetical and arbitrary example how 80% of active funds (and an even larger percentage of active investors) can exceed a market return after fees and transaction costs in a given year (Nelson 2016).

## Figure 2: Measuring Stock Returns at the Investor Level

| Fund Type | Number of Investors in Fund | 1-Jan | 31-Dec -- prior to the deduction of fees | Total Gain -- prior to the deduction of fees | Fees | Total Gain after Fees | Active Gross Return | Active Net Return | % of Active Investors Earning Active Net Return |
|---|---|---|---|---|---|---|---|---|---|
| Active Fund 1 | 100 | 1,000.0 | 1,212.0 | 212.0 | 12.1 | 199.9 | 21.2% | 20.0% | 12.2% |
| Active Fund 2 | 100 | 1,000.0 | 1,212.0 | 212.0 | 12.1 | 199.9 | 21.2% | 20.0% | 12.2% |
| Active Fund 3 | 100 | 1,000.0 | 1,212.0 | 212.0 | 12.1 | 199.9 | 21.2% | 20.0% | 12.2% |
| Active Fund 4 | 100 | 1,000.0 | 1,212.0 | 212.0 | 12.1 | 199.9 | 21.2% | 20.0% | 12.2% |
| Active Fund 5 | 100 | 1,000.0 | 1,212.0 | 212.0 | 12.1 | 199.9 | 21.2% | 20.0% | 12.2% |
| Active Fund 6 | 100 | 1,000.0 | 1,212.0 | 212.0 | 12.1 | 199.9 | 21.2% | 20.0% | 12.2% |
| Active Fund 7 | 100 | 1,000.0 | 1,212.0 | 212.0 | 12.1 | 199.9 | 21.2% | 20.0% | 12.2% |
| Active Fund 8 | 100 | 1,000.0 | 1,111.0 | 111.0 | 11.1 | 99.9 | 11.1% | 10.0% | 12.2% |
| Active Fund 9 | 10 | 100,000.0 | 98,000.0 | -2,000.0 | 980.0 | -2,980.0 | -2.0% | -3.0% | 1.2% |
| Active Fund 10 | 10 | 100,000.0 | 95,000.0 | -5,000.0 | 950.0 | -5,950.0 | -5.0% | -6.0% | 1.2% |
| Total Active Investors (aggregate) | 820 | 208,000.0 | 202,595.0 | -5,405.0 | 2,026.0 | -7,431.0 | -2.6% | -3.6% | 100.0% |
| Total Active Investors (average) | | *Weighted average return of all active individual investors (18.2%) ----------->* | | | | | | **18.2%** | 100.0% |
| | | *Aggregate net percentage return is greater for passive (-2.6%) than active (-3.6%).* | | | | | | | |

| Fund Type | Number of Investors in Fund | 42,736.0 | 43,100.0 | Total Gain | Fees | Total Gain after Fees | Passive Gross Return | Passive Net Return | % of Passive Investors Earning Passive Net Return |
|---|---|---|---|---|---|---|---|---|---|
| Index Fund (aggregate) | 300 | 50,000.0 | 48,700.7 | -1,299.3 | 1.0 | -1,300.3 | -2.6% | -2.6% | 100.0% |
| Total Passive Investors (aggregate) | 300 | *Aggregate gross percentage return is equal for both active and passive (-2.6%).* | | | | | | -2.6% | 100.0% |
| Total Passive Investors (average) | | *Average active investor's return (18.2%) is greater than the average passive investor's return (-2.6%).* | | | | | | **-2.6%** | 100.0% |

*Notes:* By illustrating how both the majority of active funds and the majority of investors can outperform a broad market index, this figure shows how the syllogisms of Sharpe (1991) and Bogle (1999) may not be perfect representations of the stock market on the investor level.

In the example above, there are 10 actively-managed funds (Active Fund 1, Active Fund 2, and so on) and one index fund (Index Fund). The stock market, as measured by the gross return of the 'Index Fund' fell approximately 2.6%, matching the aggregate gross decline of all actively-managed funds (-2.6%). We have assumed in such an example that active funds, in aggregate, performed worse than the 'Index Fund,' consistent with such syllogisms, as a result of the deduction of fees and expenses. Such a comparison, however, matters little to the investors of either Active Fund 1, or Active Fund 2, or Active Fund 3 and so on through Active Fund 8, all of which outperformed the return of the Index Fund.

In the hypothetical illustration, 80% of active funds outperformed the return of the 'Index Fund' after fees and expenses, and active funds generated an average return for each of their investors of 18.2% (including the poor performance from Active Fund 9 and Active Fund 10), even as the aggregate net return of active funds was -3.6%, below that of the aggregate net return of -2.6% for the 'Index Fund,' again due to the deduction of fees and expenses. As the number of investors that held Active Funds 1-8 significantly exceeded the number of investors that held Active Funds 9-10, as shown in the example, a far greater percentage of active investors outperformed the 'Index Fund' after fees and expenses than even the percentage of active funds that did. One might suggest that a more logical pie theory of the stock market might consider averages and read from the perspective of the investor, as follows.

**Figure 3: Nelson's Syllogism of the Stock Market**

1. All investors own the stock market.

2. The aggregate returns of all investors after all fees and expenses do not equal the average returns of all investors after all fees and expenses (as shown in Figure 2).

3. In any given year, the probability that the average return of all investors after all fees and expenses will be more or less than the aggregate return is not defined. Each passing year has a unique outcome, independent of the past.

4. The percentage of investors outperforming the index after all fees and expenses can be greater or less than the percentage of investors underperforming the index after all fees and expenses in any given year, every year (Nelson 2016).

*Notes:* We make Sharpe's and Bogle's syllogisms better, extending them to the perspective of the investor and considering analysis with respect to the performance of mutual funds relative to indexes (*Common Sense on Mutual Funds*; time period: 1963-1998, Bogle 1999).

It is not immediately clear why both syllogisms (Sharp 1991, Bogle 1999) view the market in terms of dollars and aggregates, respectively, and not on the investor level. In the work of Sharpe (1991), the possibility of active outperformance is mentioned, but the work falls short of extending the view that those that may "manage a minority share of the actively managed dollars" can also possibly comprise a majority share of investors. In *Common Sense on Mutual Funds*, Bogle reveals that during the years 1963-1998, the S&P 500 Index outperformed the majority share of mutual funds in 8 more instances than it was outperformed by the majority share of mutual funds over the 36-year period. If only four years out of 36, for example, had gone the other way, the distribution between active and passive outperformance would be even. Bogle notes there were also three major periods in which the S&P 500 Index lagged the average return of a mutual fund during the time period studied, 1965-1968, 1977-1980, and 1991-1993 (Bogle 1999).

It may be clear that the case for indexing could be compelling at certain points during the economic cycle, but it is not an absolute certainty, or a "self-evident certainty," as in Bogle's words (Bogle 1999). Indexing's popularity recently may instead be a function of misunderstood randomness or the drivers behind the gambler's fallacy, perhaps exacerbated by the presence of recency bias, as more than 90% of large-cap, mid-cap, and small-cap managers have trailed their respective benchmarks over the 15-year period ending December 2016 (Soe 2017). In any case, the statistical dynamic illustrated in Figure 2, where both the majority of funds and the majority of investors can outperform the return of a broad market index, and empirically revealed in Bogle's text *Common Sense on Mutual Funds*, where both mutual funds and index funds have outperformed each other for extended and over different periods of time, may be more common than contemporary views may believe. In the zero-sum game of baseball, for example, where either one team wins or one team loses a game, there are recurring annual instances where there are fewer teams with losing records (those with more losses than wins) than winning or average records (those with more wins than losses or those with an equal number of wins and losses). In the 15-year period ending 2014, for example, the outcome happened in 2012, 2010, 2009, 2008, 2007, 2005, 2004, 2003, 2001, and 2000, or two thirds of the time. In 2003, 18 teams had a winning record and only 12 a losing one (Baseball 2015).

Regardless of the many reasons for the rise in indexing's popularity and the growth in passively-managed assets, a discussion beyond the scope of this work, some well-respected investors' theses on market behavior have been evolving. *The New York Times* reported June 22, 2017, for example, that now the chief investment advisor for Wealthfront, Burton G. Malkiel is championing a new strategy that "aims to exploit market inefficiencies and beat the passive approach (Stewart 2017)." The article says Malkiel isn't "abandoning the essence of (his) long-held belief in passive investing," but Malkiel's firm Wealthfront will be focusing on value and momentum factors, two very integral factors in this study, as well as a few others (high dividend yields, low market beta, and low volatility). *The New York Times* had the following to say about recent developments in academic research (italics added).

> A large and growing body of academic research suggests there are market anomalies that can be exploited to beat a strict index approach. Some of that research has been recognized with Nobels in economic science — William F. Sharpe in 1990 and Eugene F. Fama in 2013. One of these findings is that *value outperforms growth*, rewarding those who identify stocks with lower price-earnings ratios and other metrics that suggest they're undervalued. *Another factor is momentum*, in which stocks that are already outperforming market averages continue to do so.

No matter the contemporary academic view or popular opinion about active or passive investing, or the likelihood of fund managers beating the market return consistently or not, or whether such performance may be luck or skill, that some very influential investors (e.g. Malkiel) continue to adapt to new market-related evidence offers one very important consideration: the field of finance may still be much too young to draw definitive conclusions about what it thinks it might know about stock market returns, as even widely-held beliefs of the early 21$^{st}$ century may not hold over the long haul when presented with new and different kinds of data in the coming decades and centuries. This we say with confidence, as even interpretations about the stock market itself can be vastly different under trough- and non-trough cycle analysis, measured at points less than one decade apart from each other.

> As of June 30 (2009), U.S. stocks have underperformed long-term Treasury bonds for the past five, 10, 15, 20 and 25 years. Still, brokers and financial planners keep reminding us, there's almost never been a 30-year period since 1802 when stocks have underperformed bonds (Zweig 2009).

An interpretation of stock market returns during the depths of the Financial Crisis (a trough-cycle assessment, June 2009) like the one above would differ vastly from any assessment about the stock market today, in mid-2017 (a non-trough cycle assessment), given that market prices are vastly above long-term historic valuation norms. As of August 2017, the forward 12-month price-to-earnings ratio for the S&P 500 is 17.4, above the 5-year and 10-year averages of 15.4 and 14, respectively (Butters 2017). When it comes to finance, how and over what time period a study is measured is just as important as what and in what way (the data) the subject is measured in the study. Contemporary academic views and popular opinion will continue to evolve, and it may only be logical to assume, by extension, that so must the data.

*The data through which market phenomena are explained may be inadequate*

Throughout history, scientists have had little choice but to explain phenomena with the tools, experiences and data they have currently available. For example, in the 16th century, most observed that the Earth appeared to be unmoving, and that the Sun revolved around the Earth (the geocentric model). The data that scientists might collect and observe at the time might have supported such a finding, and they then might have explained what they were observing in terms of the data that could be measured, or that they had. In Portuguese cosmographer Bartlomeu Velho's work of a Ptolemaic geocentric system (1568), for example, data revealing the distances of celestial bodies to the center of the Earth and the times of revolution *around the Earth* were revealed, but might Velho have thought differently and maybe even used different data had he had access to Galileo's telescope, invented in 1609?

We take for granted today that the Earth orbits the Sun, but it took centuries and Nicolaus Copernicus, on his deathbed, for such a phenomenon presented in his book, *De Revolutionibus Orbium Coelestium*, published in 1543, to become widely-accepted. Copernicus' model that established the concept of a heliocentric solar system wasn't completely correct either, but it laid the groundwork for those after him to continue to study certain conditions that may not have been easily explained through the tools, experiences, and the data of the day. Over time, however, as new theories (Einstein's general relatively) and more and different kinds of data have become available, we are now able to model black holes and even the precession of Mercury's orbit through experimental validation. Unlike the field of physics, the field of finance is comparatively much younger.

Nobel laureate Merton Miller has said that "finance in its modern form really dates only from the 1950s (Miller 1999)." Where it has taken hundreds of years from Copernicus to Einstein to better our understanding of the field of physics, by comparison there have really only been a few decades of research in finance. Even the collection of financial data doesn't stretch back that far. For example, "the first systematic collection of stock market prices, in fact, was compiled under the auspices of the Alfred Cowles Foundation in the 1930s (Miller 1999)," and there is substantial criticism of studies that use centuries old data to draw any sort of conclusions, namely some of Jeremy Siegel's findings in *Stocks for the Long Run*: "There is just one problem with tracing stock performance all the way back to 1802: it isn't really valid (Zweig 2009)." If perhaps best exemplified by Burton G. Malkiel's flexible thinking over the years, there is still a lot to discover in finance, and in this spirit and with an open mind, we write.

Our initial work in combining value and momentum data within individual stocks in backtested studies (Nelson 2012) was admittedly rather limited for two reasons. First, even though finance is still a relatively young field, researchers have been number-crunching similar databases for more than 50 years (that's still a long time for the same data sets). Second, we felt at the time that some data, namely book-to-market, can have inadequacies. We have generally been wary of using historical accounting data within the valuation context (as value is a function of the future), and we have generally been most concerned about using accounting book equity as part of any value factor assessment for operating, non-financial entities. There are instances, for example, where accounting book equity can be negligible or even negative for important and widely-known companies that have tremendous intrinsic value, and Boeing (BA) is a unique and high-profile example.

**Figure 4: Boeing's Negative Shareholders' Equity**

| | | |
|---|---|---|
| Total Boeing shareholders' equity | **2,128** | (1,294) |
| Noncontrolling interest | **97** | 152 |
| **Total shareholders' equity** | **2,225** | (1,142) |
| **Total liabilities and shareholders' equity** | **$ 62,053** | $ 53,779 |

*Notes:* An illustration of the concern that may arise by either incorporating companies with negative accounting book equity in studies, or omitting them--either the data may not measure what researchers believe it measures or highly important companies such as Boeing (BA), for example, a component of the Dow Jones Industrial Average, may be excluded from studies, in whole or in part. Image Source: Boeing's 10-K, 2009.

By extension, we have generally been skeptical of the uses of the dividend discount model to help support the application of book-to-market. While it may be reasonable that the value of a company may theoretically be a function of all "dividends (cash)" returned to shareholders (such that the company eventually ceases to exist, has nothing left), the dividend discount model often may not be practical, or even logical, given the concept of the time value of money. Berkshire Hathaway (BRK.A, BRK.B), for example, has never paid a dividend, and even if we assume that it will, the value of Berkshire Hathaway in 1970, for example, could not practically or logically have been a function of its speculated, expected future dividends in 2025, for example (if Berkshire Hathaway begins paying dividends at that time, or decides to liquidate and provide a one-time dividend at that time). The same might be said of Apple (AAPL), where the estimated value of its equity in 1990, we reason, practically and logically, had little to do with its speculated, expected dividend profile today, in 2017. We think the concept and timing of future expected enterprise free cash flows makes a lot more sense, not only in intrinsic equity value estimation but also in the measurement of any value factor.

If 16th century scientists had today's latest and greatest telescope (or if Statcast had been around since the dawn of baseball), in the same spirit, we posit that if the financial industry had data on calculated price-to-fair value ratios of stocks dating back to the 1930s or earlier, as derived by enterprise free cash flow models, value factor assessments might be more appropriately measured on the basis of price-to-fair-value ratios, or pure metrics of the difference between market price and estimates of intrinsic value, instead of book-to-market ratios or even price-to-earnings ratios (as stocks with high price-to-earnings ratios can be undervalued). Research surrounding the "predictive power of fair value estimates," or price-to-fair value ratios, is only in its infancy, but early results are very encouraging (Miller 2013). We think the enterprise free cash flow model, as opposed to the dividend discount model (given its timing issues) and the price-to-earnings ratio (given its inconclusive nature) and other valuation multiples, may be the more useful measure of any value factor in operating, non-financial equities. The enterprise free cash flow model says the market value estimate of a stock is the present value of expected future enterprise free cash flows, adjusted for balance sheet impacts.

**Figure 5: The Enterprise Free Cash Flow Model**

$$\text{Fair value} = \left[\sum_{t=0}^{\infty} \frac{A(t)}{(1+d)^t} - B(0) - C(0) + D(0)\right]$$

where A (t) is an Enterprise Free Cash Flow (1) at year t,

B (0) is a Total Debt at time 0,

C (0) is a Preferred Stock at time 0,

D (0) is a Total Cash at time 0,

d is Weighted Average Cost of Capital (WACC).

*Notes:* This figure defines the basic structure of the enterprise free cash flow model in deriving enterprise value, which is then divided by shares outstanding, to arrive at a fair value estimate per share. The company's share price is then compared to a fair value estimate to determine a price-to-fair value (P/FV) ratio. A price-to-fair value ratio, which includes enterprise valuation, differs from other valuation multiples, including enterprise value-to-EBITDA (EV/EBITDA), or EBITDA to total enterprise value (EBITDA/TEV), which do not directly compare a company's share price with estimates of its intrinsic value, and therefore are not "true" measures of price versus value. The price-to-fair value ratio, augmented by a margin of safety, is the first component of the Valuentum Buying Index.

It can therefore be reasoned that, where high book equity relative to market prices might identify an undervalued stock (one with a low price-to-book ratio), high fair value estimates relative to market prices might be a better way of identifying an undervalued stock in that such an enterprise free cash flow model avoids the shortcomings of historical accounting data (e.g. negative book equity in the case of Boeing), and therefore, may be a better way of measuring the value factor. As price-to-fair-value ratio data continues to be collected, in coming decades, price-to-fair value ratios may and probably should replace book-to-market ratios, price-to-earnings ratios and other measures to assess a value factor across rigorous academic studies, perhaps in efforts to better study what researchers think they are studying. Though a residual income model is used to value banking-related entities, the Valuentum Buying Index employs an enterprise free cash flow valuation model, enhanced through a margin-of-safety discipline, and forward comparisons of a company's price-to-earnings ratio and price-earnings-to-growth ratios versus peers as a two-pronged, contingent adaptive value factor (Nelson 2011). Though we have our opinion of how to measure a value factor, the best way to do so in any study will always be up for debate.

> How to define value and utilize it in the best possible way is subject to continuous discussion. A range of simple key ratios like P/B and P/E to the most complex cash-flow models have been suggested, analyzed and assessed. There is not one valuation method that at any time is superior to others with respect to predicting future outperformance…it is also evident by empirical studies that almost no matter how value is measured, value investing has generated superior long- term returns (Christensen 2015).

A similar exploration of the lack of authority of a momentum factor is also worthwhile. For example, is a momentum factor best captured by calculating the pricing performance of a stock during a historical 12-month period as academic studies imply--or is another time period, or better yet, another sequence of time periods yet to be discovered, more reflective of the characteristics of a momentum factor. Nobel laureate Eugene Fama has said, "of all the potential embarrassments to market efficiency, momentum is the primary one (Truitt 2013)." Uniquely, in our previous work, we measured a momentum factor by sorting a data set by the stock's trailing 2-year return through the beginning of the initial measurement period, and then used that information combined with a value proxy to assess share-price performance over multi-year periods on a go-forward basis, from January 2002 through May 2012 and from January 1995 through May 2012, respectively (Nelson 2012). Such analysis revealed that stocks with value and multi-year momentum qualities within them can also outperform over sustained periods of time. Our methods within the Valuentum Buying Index consider a variety of technical/momentum indicators in measuring a momentum factor, but there remains no definitive way to measure momentum either.

> The debate about how to measure momentum has case with value, no single definition has turned out to be superior in any market for any period of time. Many variants of price momentum have been examined, but as was the case with value, no single definition has turned out to be superior in any market for any period of time (Christensen 2015).

Since Valuentum's inception in 2011, concurrent with providing ongoing stock research coverage for a large basket of equities, we've sought to collect and generate metrics that we feel better capture specific factors that might better explain expected stock performance. We have hypothesized for some time that future expected stock returns can be explained in part by the stock-selection methodology, the Valuentum Buying Index, which captures both value and technical/momentum qualities within individual equities at particular points in time. Though an extensive explanation of the methodology is beyond the scope of this paper (including enterprise free cash flow valuation, the application of the margin-of-safety concept, and the technical/momentum indicators considered)--we have appended the methodology document to this study--the sorting mechanism of the Valuentum Buying Index between the highest ratings (10, 9-10) and lowest ratings (1, 1-2), or the Valuentum factor, the measurement of the value-timing (9-10 less 8) and ultra-momentum factors (2 less 1), and an ongoing exploration of the outperformance of equities with a number of overlapping and compensated factors within them (10 less universe) are what we seek to deliver critically in these writings.

*Some takeaways on value, momentum, and value-momentum portfolios*

> For value investors, the sweet spot in investing is being able to buy an undervalued stock right before its value is recognized by the market and just before its stock price begins to take off. But how can a value investor tell when a stock is in the sweet spot? The answer, according to Brian Nelson, president of investment research company Valuentum Securities, is to identify stocks with good value that are just starting to exhibit good technical/momentum characteristics.
>
> Doing so helps an investor avoid:
>
> • value traps: stocks whose prices continue to fall—so called "falling knives"—or stocks whose value will never be recognized by the market,
>
> • underperformance due to the opportunity cost associated with holding a stock with great potential, but whose value takes an inordinate amount of time to be recognized by the market and
>
> • speculative momentum or irrational high-yielding stocks whose technicals are unsupported by their fundamental valuation ("greater fool" stocks). (Truitt 2013).

With our concerns--about data, which data, and whether such data measures what it says it measures--clearly presented, there are three takeaways from decades of research in finance that are worth noting, we accept, and are relevant to this paper. First, from Asness 2009, it is widely-documented that value stocks outperform growth stocks. Second, it has also been observed that stocks with high positive momentum outperform stocks with low positive momentum (Stattman 1980, Fama-French 1992, Jegadeesh and Titman 1993, Asness 1994, Grinblatt and Moskowitz 2004). Third, research has concluded that a portfolio consisting simply of 50% of a long-short value-oriented portfolio and 50% of a long-short momentum-oriented portfolio can generate better risk-adjusted ratios and lower volatility than either value or momentum by themselves (Asness 2009).

In previous work (Nelson 2012), we strove to answer the question: What are the types of stocks that drive such outperformance of a combined long-short, value-momentum portfolio?" We hypothesized that, within a combined value-momentum portfolio, as presented originally by Asness (2009), the overweighting of the embedded subset of stocks that had both good value characteristics and good momentum characteristics were the key drivers behind the outperformance on the long side of such a portfolio, and conversely, we hypothesized that the overweighting of the embedded subset of stocks that had both poor value characteristics and poor momentum characteristics were the key drivers behind outperformance on the short side of such a portfolio. We hypothesized that the overweighting of these two subsets represented the major drivers of outperformance behind the combined value and momentum portfolio.

We illustrated our hypothesis by identifying and highlighting outperformers in a combination portfolio of our own making--a 'Valuentum' portfolio--using historical fundamental and pricing data of non-financial firms in the Dow Jones Industrial Average (Nelson 2012). We used the widely-known index as a way to hone in on and identify the qualities of such stocks that may be key performance drivers behind such a value-momentum combination portfolio's abnormal returns. In our work, we defined stocks that were overweighted on either side of the portfolio, the ones accounting for such significant outperformance in a 'Valuentum' portfolio, as 'Valuentum' stocks: stocks on the long side that are both undervalued and exhibit bullish momentum characteristics and stocks on the short side that are both overvalued and exhibit bearish momentum characteristics.

We noted that previous academic works have examined the efficacy of value and momentum separately and within one asset class at a single point in time and have analyzed value and momentum together from a long-short portfolio perspective across asset classes, but in our study, we outlined the potential benefits of investing in (shorting) a cohort of stocks with both good (poor) value and good (poor) momentum qualities within them. We also revealed that stocks that have both good value and good momentum qualities within them can generate abnormal returns relative to stocks that have poor value and poor momentum qualities within them and that a 'Valuentum' portfolio can consistently outperform value, growth, momentum and combined growth-momentum portfolios over various time periods (Nelson 2012).

As outlined in the three brief instances explained in this paper (Miller, Daftary, Buffett), we have also long hypothesized that stocks that are attractive across the investment methodology spectrum--including, but not limited to, value and momentum, two widely-documented compensated factors--may have the greatest probability of capital appreciation and relative outperformance (e.g. Alpha Architect on Peter Lynch). On the other hand, we have long believed that the worst stocks will be shunned by most investment disciplines and display expensive valuations, poor technicals and deteriorating momentum indicators. We have tended to like stocks that have good value characteristics and good momentum characteristics within them (stocks with the highest Valuentum Buying Index ratings, generally 9 or 10 on the scale), while we have tended to dislike stocks that have poor value characteristics and poor momentum characteristics within them (stocks with the lowest Valuentum Buying Index ratings, generally 1 or 2 on the scale).

In previous work, we have also suggested that another potential benefit of a combined value and momentum process within individual stocks is that it may allow for improved entry and exit points on the most undervalued stocks, pointing to the foundation for the development of a potential value-timing factor. For example, in *The Case for the Valuentum Style of Investing*, we posited that "future research may confirm that the greatest outperformance of undervalued equities may occur in immediate subsequent periods following an improvement in their underlying technical and momentum indicators (Nelson 2011)." Academic studies seemingly reinforce our view of the powerful risk-reward potential of investing in stocks that have both good value and good momentum characteristics within them:

> …based on data from the US stock market from 1965-2009…a strategy which combines value and momentum…consists of the 25 stocks with the best six-month price momentum within the universe of the highest ranking value stocks. This strategy has clearly outperformed the value strategy and without any noticeable change in the risk profile (Christensen 2015; O' Shaughnessy 2012).

In the past, our ability to rigorously test the Valuentum Buying Index rating system has been limited by the lack of available internally-generated data (namely enterprise-value-derived price-to-fair value ratios), but preliminary testing of the Valuentum Buying Index during the past several years has supported many of our hypotheses. The simulated performance of the Best Ideas Newsletter, for example, continues to generate outsize returns (Nelson 2017), the sorting efficacy of the Valuentum Buying Index among original Best Ideas Newsletter constituents has been notable (Nelson, 2014b), and a random case study that captured a snapshot of 570 Valuentum Buying Index ratings in September 2013 and their ability to sort stocks through September 2014 was meaningful (Nelson 2014a). For relevant and pertinent background to the subsequent time series study in this paper, we have republished with edits the 2013-2014 case study in this work, as follows.

## II. Case Study of Valuentum Buying Index Ratings (2013-2014)

*A study of the performance of one cohort of Valuentum Buying Index ratings from one point in time to another point in time.*

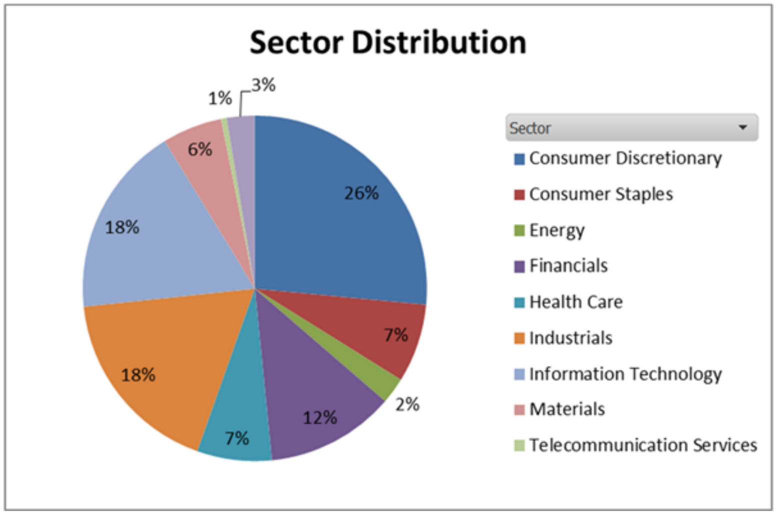
Valuentum was selected by an institutional money manager to assign Valuentum Buying Index ratings individually to companies in a portfolio of 570 stocks. The companies were provided to Valuentum directly from the institutional money manager. Valuentum did not have any prior knowledge of the companies or any of their qualities with respect to such items as market capitalization, sector, industry, etc. In no way did Valuentum have any influence over the selection of the companies. The Valuentum Buying Index was targeted for portfolio optimization and weighting considerations with no time horizon defined.

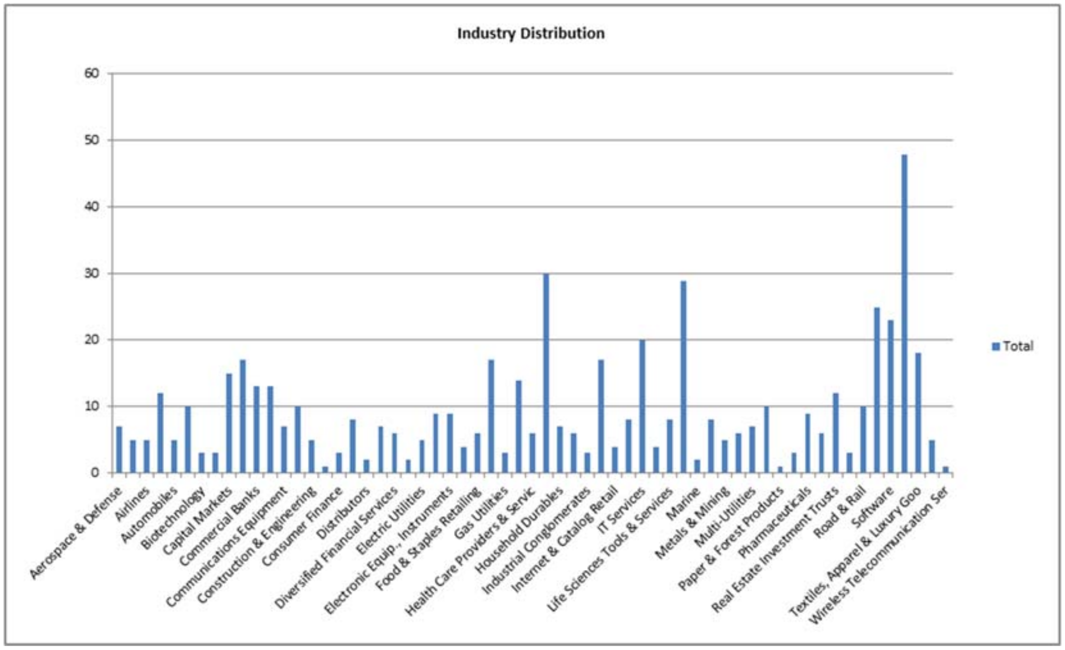
*Case Study - Universe*

The stocks assigned to Valuentum totaled 570. The sector and industry distributions are displayed below. Where complete data is available, the average of the last fiscal year revenue for the stocks selected was approximately $13 billion, with a range of $438.2 billion (b) to $39.8 million (m). The average market capitalization for companies included in the study was $26.1 billion, with a range of $662.9 billion (b) to $214 million (m). Roughly two thirds of the companies included in the study paid a dividend, with the average yield of ~1.9% for those paying a dividend. The descriptive statistics are approximate of the group at the end of the study, September 30, 2014. The universe spanned all sectors, industries, market capitalizations, and dividend characteristics.

**Figures 6, 7, 8: Sector and Industry Distributions of Stocks in Case Study**

| Row Labels | Count of Sector |
|---|---|
| Consumer Discretionary | 151 |
| Consumer Staples | 42 |
| Energy | 14 |
| Financials | 69 |
| Health Care | 40 |
| Industrials | 102 |
| Information Technology | 102 |
| Materials | 32 |
| Telecommunication Services | 3 |
| Utilities | 15 |
| **Grand Total** | **570** |






*Notes:* These figures reveal the distribution of companies in the case study, sorted by major sector and industry category.

*Case Study - Methodology*

The Valuentum Buying Index ratings assigned to the stocks in the case study ranged from 1 through 9, with no stock registering the highest rating of a 10 in the study. The number (count) of Valuentum Buying Index ratings are shown and arbitrarily aggregated into the following five cohorts (9-10, 7-8, 5-6, 3-4, 1-2) below for the case study. We discuss different cohorts for Valuentum Buying Index ratings in the time series analysis.

**Figures 9, 10: Valuentum Buying Index Distribution of Stocks in Case Study**

| Valuentum Buying Index Ratings | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **9** | **8** | **7** | **6** | **5** | **4** | **3** | **2** | **1** |
| 1 | 3 | 65 | 242 | 46 | 87 | 112 | 5 | 9 |

| Valuentum Buying Index Ratings | | | | |
|---|---|---|---|---|
| **9-10** | **7-8** | **5-6** | **3-4** | **1-2** |
| 1 | 68 | 288 | 199 | 14 |

*Notes:* These figures reveal the distribution of companies in the case study, sorted by Valuentum Buying Index rating.

Valuentum Buying Index ratings do not fit to a normal distribution. The Valuentum Buying Index is a function of 1) a firm's cash-flow-derived intrinsic value estimate via a forward-looking enterprise free cash flow process, augmented by the margin-of-safety concept, 2) a relative valuation assessment versus peers (using forward price-to-earnings and forward price-earnings-to-growth ratios), and 3) a technical/momentum assessment. The better that we think a company registers with respect to each of these three criteria, the higher the Valuentum Buying Index rating. The Valuentum Buying Index is systematically generated, but it considers a variety of qualitative and quantitative dynamics.

For example, an analyst might think about qualitative dynamics such as industry structure and competitive advantages in assigning the fair value ranges around a company's cash-flow-derived intrinsic value estimate, which then influences whether a firm is undervalued or overvalued on a discounted cash-flow basis, the first pillar of the process. Within the second pillar of the Valuentum Buying Index, an analyst thinks about the qualitative dynamics that influence mid-cycle revenue growth and profitability, which in turn influences the 5-year forward price-to-earnings-growth ratio, which is used with the forward price-to-earnings ratio in a relative valuation overlay. A systematically-applied assessment of the attractiveness of the stock from a technical/momentum standpoint rounds out the third pillar, which in theory, adds market-based conviction to the fundamental valuation assessment.

The Valuentum Buying Index combines forward-looking qualitative and quantitative metrics to arrive at a single numerical outcome/score/rating (10=best, 1=worst). The Valuentum Buying Index ratings cannot be generated by any other firm. The process is proprietary and Valuentum is trademarked.

*Case Study - Results*

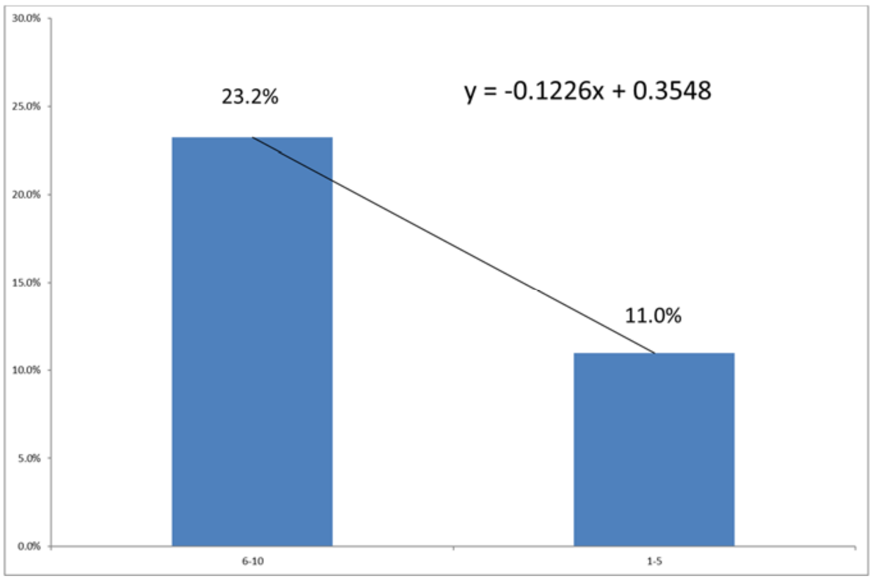
The time period of the case study was September 30, 2013, through September 30, 2014. The Valuentum Buying Index ratings at the beginning of the study were recorded, and this universe of 570 Valuentum Buying Index ratings comprised the study. The return information for the selected companies over this period was provided independently to Valuentum from cloud service provider Xignite. The return information does not include dividends paid over the time period. Stocks that were no longer listed on any exchange at the end of the measurement period, as a result of buyouts, were excluded from the study.

In the graphs below (Figures 11, 12, 13), the methodology for calculating the average return of each cohort (e.g. 5-6) was to take the average of the average return of companies registering the same Valuentum Buying Index rating. For example, the returns of companies that registered a rating of 5 were averaged (11.2%), and this average return and the average return for companies registering a 6 (15.4%) were then averaged to arrive at the 13.3% average return for the 5-6 cohort. In the High-versus-Low chart (Figure 11), the average of the average individual returns for ratings of 6, 7, 8, 9, and 10 were compared to the average of the average returns for ratings 1, 2, 3, 4, and 5.

In the three representative graphs below (Figures 11, 12, 13) of the case study, there is generally strong behavior tying higher Valuentum Buying Index ratings with better returns and lower Valuentum Buying Index ratings with lower returns. In the case study, the Valuentum Buying Index also ranked the average returns of the individual ratings from 9 through 4 (9, 8, 7, 6, 5, 4).

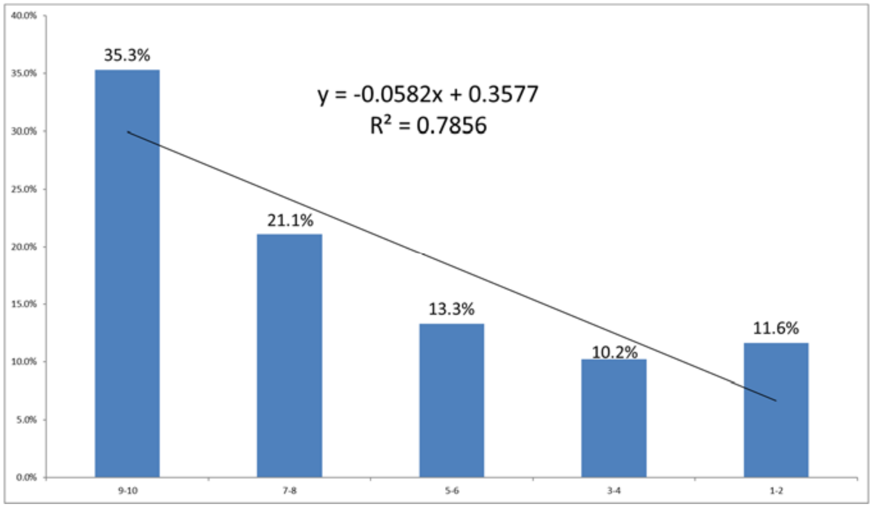
Said differently, it sorted the return differential of the average returns of companies that registered a 9 from companies that registered an 8 from companies that registered a 7 and so on. The sum of the number of stocks that registered a rating of 9 through 2, excluding the ratings of 3 and 1 (i.e. 9, 8, 7, 6, 5, 4, and 2) included 449 firms, or ~79% of the companies assigned. Note that in the case study, stocks rated 2 did not outperform stocks rated 1, a tendency that is different than that observed in the more comprehensive time series study that follows.

**Figure 11: Returns of High Valuentum Buying Index Ratings versus Low in Case Study**



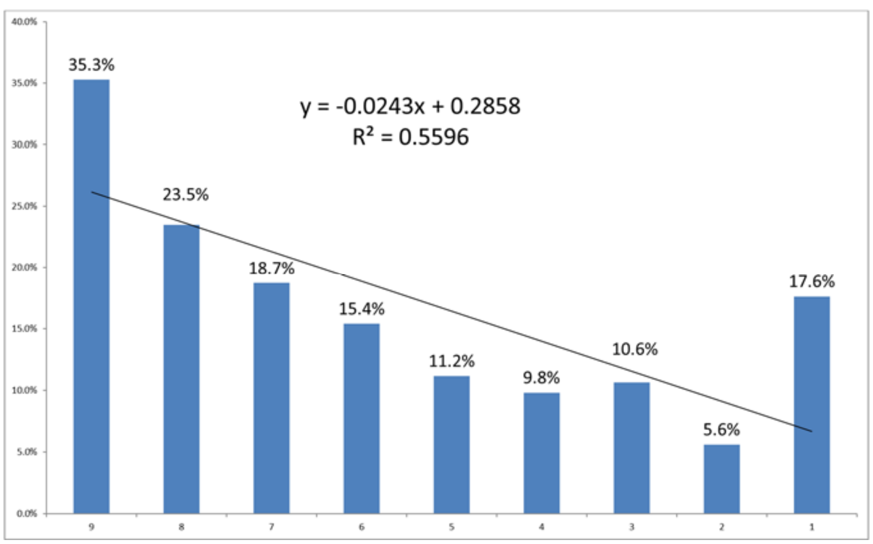

*Notes:* This figure reveals the average of the average returns of high Valuentum Buying Index rated stocks (6-10), left, versus low Valuentum Buying Index rated stocks (1-5), right, measured at September 2013 through September 2014. In the case study, the Valuentum Buying Index showed the ability to rank average returns over the specific measurement period, using 570 Valuentum Buying Index ratings collected in September 2013.

**Figure 12: Returns of Valuentum Buying Index Ratings By Cohort in Case Study**




*Notes:* This figure reveals the average of the average returns by arbitrarily-defined cohort of the case study (9-10; 7-8; 5-6; 3-4; 1-2). In the case study, the Valuentum Buying Index showed the ability to generally rank average returns, by cohort, given the findings of a meaningfully negative slope coefficient and generally high R-squared value. The study used 570 Valuentum Buying Index ratings collected in September 2013 and measured the performance of stocks that fell in each rating cohort at the beginning of the study through September 2014.

**Figure 13: Returns of Valuentum Buying Index Ratings By Individual Rating in Case Study**



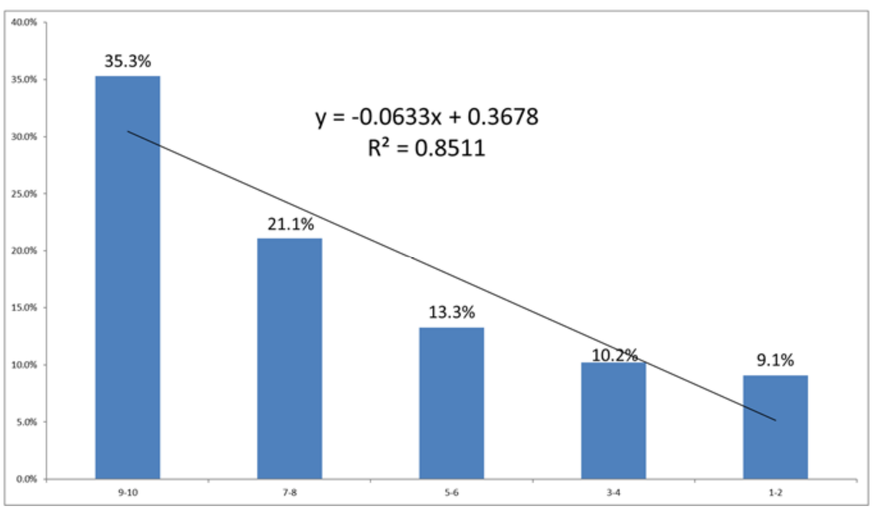

*Notes:* This figure reveals the average returns by each Valuentum Buying Index rating present in the case study. The study used 570 Valuentum Buying Index ratings collected in September 2013 and measured the average performance of stocks that registered each rating at the beginning of the study through September 2014.

*Case Study - Observations*

Though the Valuentum Buying Index showed the ability to sort average stock returns by rating with a relatively high degree of accuracy in the case study over a 12-month time period ending September 30, 2014 (Figure 13), the Valuentum Buying Index is generally designed to differentiate between rating outliers or rating extremes (i.e. the highest ratings versus the lowest ratings), not necessary sort stocks in the “big middle” of the rating distribution (3-8) on a granular basis due to contradicting expected near-term return profiles. In the case study, however, the efficacy of the Valuentum Buying Index is augmented via the application of cohorts and significantly enhanced via High-versus-Low Valuentum Buying Index analysis (i.e. R-squared increased as cohorts were formed).

We make two very important observations of the case study: 1) The time period of the case study revealed a 17.2% return on the SPDR S&P 500 ETF (SPY) from $168.01 to $197.02, and indeed, a possible scenario where overpriced stocks (generally lower rated) may have become even more overheated (higher priced). We attribute the anomaly presented by the returns of companies registering a 1 to this dynamic. 2) A particular firm registering a 2 at the beginning of the study was acquired for a substantial premium a few weeks before the end of the study. Using the pre-deal price for this company, prior to the announcement ($33.51 instead of $45.90), the average return by rating cohort would have been as follows in Figure 14.

**Figure 14: Adjusted Returns of Valuentum Buying Index Cohorts in Case Study**



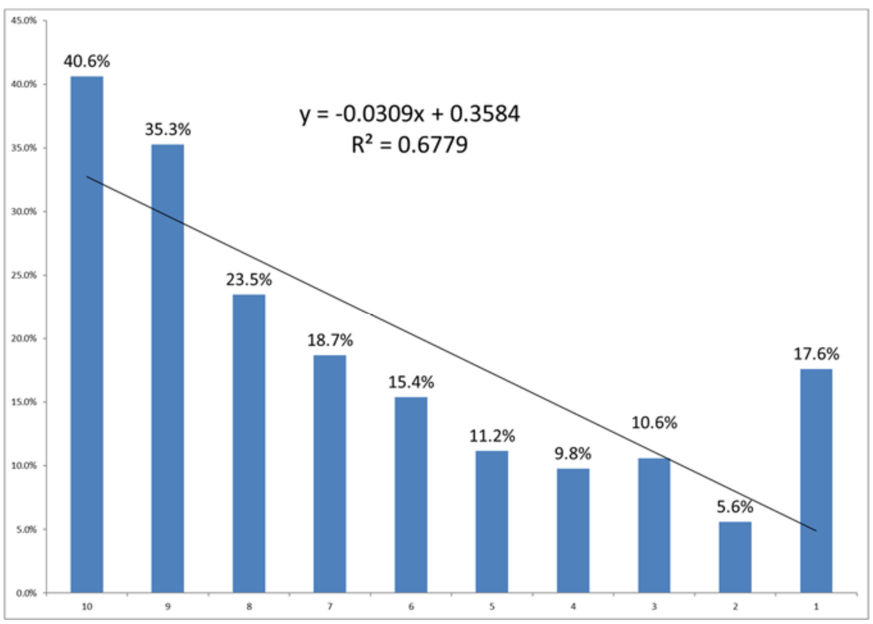

*Notes:* This figure reveals the average of the average returns by arbitrarily-defined cohort of the case study (9-10; 7-8; 5-6; 3-4; 1-2), adjusted for the price of one particular firm that had been acquired for a substantial premium shortly before the end of the study. In the case study, the Valuentum Buying Index showed the ability to generally rank average returns, by cohort, given the findings of a meaningfully negative slope coefficient and generally high R-squared value. The study used 570 Valuentum Buying Index ratings collected in September 2013 and measured the performance of stocks that fell in each rating cohort at the beginning of the study through September 2014.

*Case Study – Potential Applications*

In the case study, the Valuentum Buying Index acted as a portfolio optimization tool, differentiating outperforming stocks (9) from underperforming stocks (the balance of the universe) within a very diverse portfolio provided to Valuentum independently by an institutional money manager. The case study showed the potential efficacy and implications of using the Valuentum Buying Index as a portfolio management optimization tool (i.e. the incremental outperformance that might be attained by overweighting the highest-VBI rated stocks and underweighting the lowest-VBI rated stocks without altering stock selection).

Though not used as such in the study, the Valuentum Buying Index might also be used as an idea-generator to further enhance portfolio returns. For example, the one idea that registered a Valuentum Buying Index rating of a 10 within our coverage universe at the beginning of the study was Baidu (BIDU)--not included in the original 570 ratings. Shares of Baidu (BIDU) gained 40.6% over the time period measured ($155.18 → $218.23). Adding Baidu to the individual Valuentum Buying Index return distribution in the case study in Figure 13 significantly enhances its R-squared value while making the slope coefficient increasingly more negative, all else equal, as shown below.

**Figure 15: Adjusted Returns of Valuentum Buying Index Ratings in Case Study**



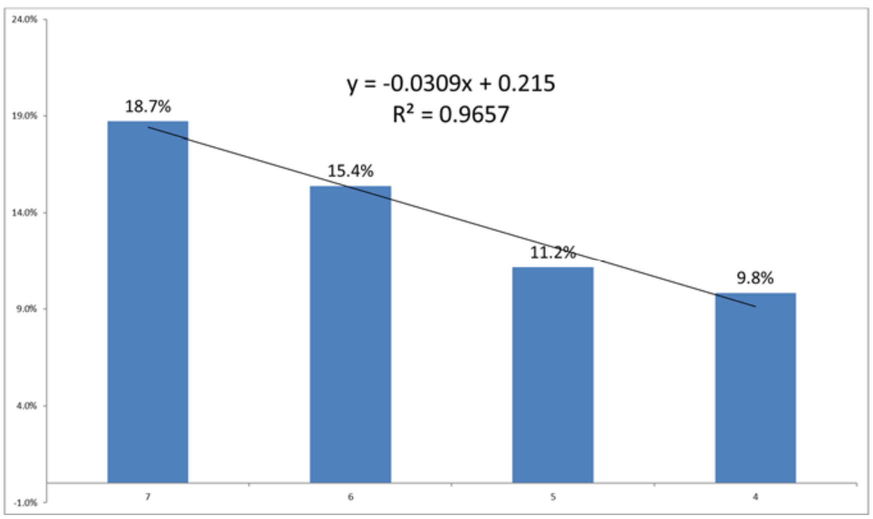

*Notes:* This figure reveals the average returns by each Valuentum Buying Index rating present in the case study, adding the return of the only represented 10-rated stock at the time of the beginning of the study, Baidu (BIDU) to the distribution, a company not included in the original 570 companies. The study used 570 Valuentum Buying Index ratings collected in September 2013 and measured the average performance of stocks that registered each rating at the beginning of the study through September 2014.

*Case Study – Limitations*

The Valuentum Buying Index tends to be highly selective in identifying outliers or extreme readings (i.e. stocks that register a 9 or 10, or stocks that register a 1 or 2). Though this may help with individual stock-selection as shown in the Best Ideas Newsletter portfolio (Nelson 2014), it may provide limitations within an overall portfolio management setting, where too much single-stock or idiosyncratic risk may be absorbed under situations where few outliers are identified.

Though the methodology is not designed to target sorting granularity among average returns in middle ratings, the ranking of the "big middle" in the case study over a 12-month period, however, also generally supported the tendency of stocks with high Valuentum Buying Index ratings to outperform those with low Valuentum Buying Index ratings. For example, there were 440 firms that registered a rating between 4 and 7 in the study, inclusive, and the general ability of the Valuentum Buying Index to sort average returns across these ratings was present with a high R-squared measure. These rankings (4-7) represented ~77% of the stocks included in the study.

**Figure 16: Valuentum Buying Index Ranking of Returns, the "Big Middle"**




*Notes:* This figure reveals the average returns by each Valuentum Buying Index rating present in the case study for a portion of the "big middle," or from individual ratings 4 through 7. The study used 570 Valuentum Buying Index ratings collected in September 2013 and measured the average performance of stocks that registered each rating at the beginning of the study through September 2014.

Whereas the case study in this work took a snapshot of Valuentum Buying Index ratings on September 30, 2013, and measured the returns of that universe of ratings 12 months into the future, September 30, 2014, the time series study that follows is a more robust evaluation, effectively measuring the returns of Valuentum Buying Index ratings at any time of any future update, irrespective of dates. In other words, the study below incorporates thousands of Valuentum Buying Index rating time series between thousands of various dates, while the case study above assessed 570 Valuentum Buying Index time series from the beginning to the end of two distinct dates. The case study above can indirectly be viewed as a subset of the time series study that follows, though pricing data will vary given the difference between share prices of companies at the end of the case study and share prices of companies updated near the end of the case study.

### III. Evaluating 20,000+ Time Series of Valuentum Buying Index Ratings

*A study of the performance of thousands of Valuentum Buying Index ratings over various points of time.*

The Valuentum Buying Index is generally used to enhance stock-selection methods, as outlined in the image that follows, to source long ideas from the highest-rated issues (9-10), "Top Pick" "We'd Consider Buying," and to source short (or put option) ideas from lowest-rated issues (1-2), "We'd Consider Selling." The findings in the 2013-2014 case study were very intriguing in the sense that the Valuentum Buying Index also effectively ranked the average returns in the "big middle," or in the rankings of 4-7, an area not necessarily targeted by the methodology and one that we describe to be less-actionable. As we outline in the Valuentum Buying Index methodology document, appended to this paper, we tend to add stocks that register a high Valuentum Buying Index rating (9-10) to the Best Ideas Newsletter portfolio, hold such stocks for some time, and tend to remove stocks from the newsletter portfolio when they register a lower, or lowest, Valuentum Buying Index rating (generally 1-2).

**Figure 17: Valuentum Buying Index Rating and Potential Action**

| VBI Score | Potential Action |
|---|---|
| 10 | Top Pick |
| 9 | We'd Consider Buying |
| 6 to 8 | Constructive (tactical add / trim) |
| 3 to 6 | Less Exciting (tactical add / trim) |
| 1 to 2 | We'd Consider Selling |

*Notes:* This figure translates each Valuentum Buying Index rating to a "Potential Action." To further illustrate much of the ambiguity of the "big middle," a rating of 6, for example, can offer a different, contradicting insight ("Potential Action") depending on other company-specific and/or stock-related considerations. Such translations were assigned at methodology inception (2011), not after any study involving the Valuentum Buying Index.

A Valuentum Buying Index rating is recorded each time that a company's 16-page stock report is updated, generally every 3-5 months, on average, but updates can be as frequent as one week or as long as a half-year or longer, depending on quarterly results or the timing of the release of material information following the latest update. There is no controlled time period for when Valuentum Buying Index ratings are updated, and as a result, the time interval (period, update), or time lapse, between Valuentum Buying Index rating updates for the same company is variable.

In the following time series study, we believe we have incorporated almost all programmatically-derived Valuentum Buying Index ratings that have ever been generated by our team, though data from companies bought out prior to 2014-2015 may be omitted, including some of the best performing, highly-rated ideas (e.g. EDAC). For the sake of presenting results of a systematic, repeatable process, free of human intervention, manually-generated Valuentum Buying Index ratings, as those included in the original edition of the Best Ideas Newsletter (Nelson 2014), have been excluded from this study.

*Time Series Study – Defining a Time Series*

**Figure 18: Sample Time Series, Baidu (BIDU)**

| BIDU Rating History | Price | Fair Value | VBI |
|---|---|---|---|
| 1-May-17 | $178.03 | $186.00 | 6 |
| 6-Jan-17 | $176.38 | $184.00 | 6 |
| 22-Jul-16 | $160.88 | $173.00 | 3 |
| 11-Mar-16 | $182.98 | $191.00 | 7 |
| 9-Oct-15 | $144.22 | $211.00 | 6 |
| 29-May-15 | $197.40 | $253.00 | 6 |
| 5-Dec-14 | $232.72 | $240.00 | 6 |
| 18-Jul-14 | $191.17 | $234.00 | 6 |
| 14-Mar-14 | $160.59 | $227.00 | 6 |
| 8-Nov-13 | $151.09 | $193.00 | 10 |
| 19-Jul-13 | $111.08 | $178.00 | 10 |
| 28-Mar-13 | $87.70 | $154.00 | 6 |
| 5-Nov-12 | $103.80 | $156.00 | 3 |
| 10-Aug-12 | $131.06 | $172.00 | 6 |

*Notes:* This figure shows how share prices and Valuentum Buying Index ratings are recorded in a time series, as defined in the time series study, as in the case of Baidu (BIDU).

Each Valuentum Buying Index rating has its own unique time series, or a sequence of returns that are measured at points that new, later Valuentum Buying Index ratings for the same company are published. For example, Baidu (BIDU) registered a Valuentum Buying Index rating of a 10 on July 19, 2013, corresponding to a price of $111.08. The returns of the various time series that correspond to that particular rating of 10 will be a function of $111.08 and the future prices of Baidu at subsequent updates [VBI rating, time interval (or end point)]: November 8, 2013 [10, 1], March 14, 2014 [10, 2], July 18, 2014 [10, 3], December 5, 2014 [10, 4], May 29, 2015 [10, 5], October 9, 2015 [10, 6], March 11, 2016 [10, 7], July 22, 2016 [10, 8], January 6, 2017 [10, 9], and May 1, 2017 [10, 10]. In the study, this particular Valuentum Buying Index rating of a 10 contributes 10 measures of returns across the respective time intervals (end points) that correspond to a rating of 10.

As another example, the returns of the time series of the Valuentum Buying Index rating of a 7 registered by Baidu on March 11, 2016 will be a function of $182.98 and the prices occurring at intervals that correspond to the subsequent dates [VBI rating, time interval (or end point)]: July

22, 2016 [7, 1], January 6, 2017 [7, 2], and May 1, 2017 [7, 3]. In the time series study, this particular Valuentum Buying Index rating of a 7 contributes 3 measures of returns across the respective time intervals (end points) that correspond to a rating of 7. However, in the case of the Valuentum Buying Index rating of 6 registered by Baidu on May 1, 2017, because no subsequent updates have occurred in the study, such a rating has no time series, and therefore, the performance of this particular rating of 6 is not included in the study. Though there is some overlap with respect to certain time series between the two data sets, in all, we studied 20,000+ time series of Valuentum Buying Index ratings spanning Valuentum's inception (2011) through mid-June 2017.

Rightsizing the return data of each Valuentum Buying Index rating to a time series has a number of unique benefits. In doing so, we believe we are better able to calculate relative and expected returns between and for each Valuentum Buying Index rating over time (as more and more data is collected in the decades ahead), respectively. Because the ratings do not conform to any defined distribution, at any time, there could be a large number of high Valuentum Buying Index ratings or a large number of low Valuentum Buying Index ratings. Theoretically, for instance, at or near stock-market peaks, the number of stocks with a Valuentum Buying Index rating of a 9 or 10 may be few, while the number of stocks with a Valuentum Buying Index rating of a 1 or 2 may be many. In targeting a sorting of future expected returns among stocks, as more and more data is collected in the decades ahead, the Valuentum Buying Index is designed to retain its relative ranking tenets and stock-selection efficacy regardless of the economic cycle. In some ways, a varying Valuentum Buying Index distribution at different points during the economic cycle is one of the methodology's key features.

As of July 21, 2017, for example, there are no 9- or 10-rated companies on the Valuentum Buying Index, while there are dozens of stocks rated 1 or 2. What this implies is that a larger percentage of our coverage universe is, at the time of this writing, registering lower ratings in anticipation of what could be lower average stock returns going forward. Because no stock currently registers a 9 or 10 on the Valuentum Buying Index at the time of this writing, the calculated expected returns of stocks registering a 9 or 10 may not be diluted in the event the market does eventually experience lower average stock returns, or even negative ones. Though it may take many market cycles to achieve increasingly more relevant readings (i.e. expected returns), by rightsizing Valuentum Buying Index ratings to time series, we think calculating relative and expected returns between and for each Valuentum Buying Index over time can be achieved, respectively, similar in some ways to how transition matrices may measure, albeit not imply, a probability of default for a respective credit rating over a particular period of time (Vazza 2015). Unlike one-year transition probability matrices, however, the duration of return measurements for each Valuentum Buying Index rating is measured at variable intervals, depending on conditions of the update cycle.

*Time Series Study – Data Sets*

Based on arbitrary data collection limitations, each data set, Data Set I and Data Set II, comprised a maximum look-back period of 14 Valuentum Buying Index ratings for each company. The data sets were not combined or fused, in part to limit the introduction of any processing errors to the study. Because each company's time series is unique and independent of any other company's time series, fusing data for companies across the data sets would require additional resources, without adding material robustness to the outcome of the study. We estimate that by fusing the data, no unique time series would be added to the overall study, but overlapping time series would be removed.

The first data set (Data Set I) included 1,082 companies spanning over 100 industry groups across all major sectors, with varied market capitalizations and dividend qualities. Within Data Set I, there contained 13,545 Valuentum Buying Index ratings with corresponding prices and enterprise free-cash-flow-derived fair values estimates, resulting in the analysis of 12,463 time series of Valuentum Buying Index ratings. Excluding banking entities, the latest Valuentum Buying Index readings for each company, or the latest reading in each individual time series, in Data Set I spanned from January 20, 2017 through June 14, 2017. The earliest Valuentum Buying Index data point in Data Set I is in early 2012.

**Figure 19: Distribution of Valuentum Buying Index Ratings in Data Set I**

Data Set I: Valuentum Buying Index Ratings

| 10 | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | 1 | Total |
|---|---|---|---|---|---|---|---|---|---|---|
| 6 | 77 | 28 | 1,401 | 5,167 | 756 | 1,730 | 4,094 | 120 | 166 | 13,545 |
| 0.04% | 0.57% | 0.21% | 10.34% | 38.15% | 5.58% | 12.77% | 30.23% | 0.89% | 1.23% | 100.00% |

| 9-10 | 6-8 | 3-5 | 1-2 | Total |
|---|---|---|---|---|
| 83 | 6,596 | 6,580 | 286 | 13,545 |
| 0.61% | 48.70% | 48.58% | 2.11% | 100.00% |

*Notes:* This figure shows the distribution of Valuentum Buying Index ratings in Data Set I, with cohorts conforming to "Potential Action," as defined in Figure 17.

The second data set (Data Set II) included 1,165 companies spanning over 100 industry groups across all major sectors, with varied market capitalizations and dividend qualities. Within Data Set II, there contained 9,798 Valuentum Buying Index ratings with corresponding prices and enterprise free-cash-flow-derived fair values estimates, resulting in the analysis of 8,634 time series of Valuentum Buying Index ratings. The latest Valuentum Buying Index readings for each company, or the latest reading in each individual time series, in Data Set II spanned from September 19, 2014 through March 16, 2015. The earliest Valuentum Buying Index data point in Data Set II is in late 2011.

**Figure 20: Distribution of Valuentum Buying Index Ratings in Data Set II**

Data Set II: Valuentum Buying Index Ratings

| 10 | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | 1 | Total |
|---|---|---|---|---|---|---|---|---|---|---|
| 12 | 100 | 13 | 1,020 | 4,013 | 571 | 1,106 | 2,790 | 74 | 99 | 9,798 |
| 0.12% | 1.02% | 0.13% | 10.41% | 40.96% | 5.83% | 11.29% | 28.48% | 0.76% | 1.01% | 100.00% |

| 9-10 | 6-8 | 3-5 | 1-2 | Total |
|---|---|---|---|---|
| 112 | 5,046 | 4,467 | 173 | 9,798 |
| 1.14% | 51.50% | 45.59% | 1.77% | 100.00% |

*Notes:* This figure shows the distribution of Valuentum Buying Index ratings in Data Set II, with cohorts conforming to "Potential Action," as defined in Figure 17.

Given the look back-periods of each data set, there are some Valuentum Buying Index ratings and some parts of time series that appear within both sets. The data sets have not been adjusted for such overlap, and therefore, have not been fused. With respect to Magna International (MGA), for example, there are only 5 new, incremental Valuentum Buying Index ratings in Data Set I than in Data Set II (10 time series). For Coca-Cola (KO), as another example, there are only 6 new, incremental Valuentum Buying Index ratings in Data Set I than in Data Set II (15 time series). However, for Boeing (BA), for example, there are 11 new, incremental Valuentum Buying Index ratings in Data Set I than in Data Set II (55 time series), and for Apple, there are 10 new, incremental Valuentum Buying Index ratings in Data Set I than in Data Set II (45 time series). We find both data sets to be useful in understanding the nature of Valuentum Buying Index ratings.

Valuentum has discretion over which companies are included in its coverage universe, which companies are assigned Valuentum Buying Index ratings, and by extension which companies are included in such data sets. We do not believe, however, that our discretion over our coverage universe generates biases in the results of the time series study, though we note our coverage universe is more heavily weighted toward mid- and large-cap stocks in the US. For example, companies comprising Data Set I, as defined later in this paper, had a range of market capitalization of $8.2 million (m) to $855 billion (b), with mean and median of $23.2 billion and $6.2 billion, respectively. We think the large number of industry groups, range of market capitalization, presence of non-US ADRs, and variety of dividend-paying and non-dividend paying stocks with various levels of yield make for very diverse data sets across many parameters.

*Time Series Study – Results*

The Valuentum Buying Index, by design, tends to be very selective with respect to which companies enter outlier or extreme cohorts. As a result, the number of data points and time series to measure the performance of Valuentum Buying Index rating outliers or extremes (e.g. 9-10, 1-2) is not as large as that of the "big middle" (3-8), neither should it nor does it have to be. As in adjusting batting averages for swings only through a hitter's sweet spot, for example, stocks that reside in the cohorts of 9-10 or 1-2 are ideas within the Valuentum "sweet spot," or those stocks that meet the criteria of good value and good momentum or poor value and poor momentum within stocks, respectively--or an increasingly number of important and compensated factors, as in the case of equities rated 10 on the index.

In both Data Set I and Data Set II, stocks with the highest Valuentum Buying Index rating (10) significantly outperformed stocks with the lowest Valuentum Buying Index rating (1) over immediate and multiple time periods with statistically significant readings, and stocks with the highest Valuentum Buying Index ratings (9-10) outperformed stocks with the lowest Valuentum Buying Index ratings (1-2) over immediate and multiple time periods, the latter comparison collectively considering several hundred Valuentum Buying Index time series. Because random performance may have been expected under efficient-market or "random walk" theory, we think the following sorting mechanism helps to support the Valuentum Buying Index as a stock-selection methodology, or a systematic framework, that helps to identify potential "winners" (10) and "losers" (1) over certain periods of time.

**Figure 21: Data Set I, Outperformance of 10s; Underperformance of 1s**

| Time Interval | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| VBI: 10 | 6.55% | 11.52% | 28.9% | 28.59% |
| VBI: 1 | 2.33% | 4.93% | 9.84% | 9.36% |
| Difference (10 less 1) | 4.2pt | 6.6pt | 19.1pt* | 19.2pt* |
| Average Return (Universe) | 3.2% | 7.82% | 14.52% | 18.29% |
| Difference (10 less average) | 3.4pt | 3.7pt | 14.4pt | 10.3pt |
| Difference (1 less average) | -0.9pt | -2.9pt | -4.7pt | -8.9pt |

*Notes:* This figure shows the average returns of stocks registering a 10 and the average returns of stocks registering a 1 in Data Set I over relevant future periods. At time intervals 3 and 4 (as measured from time 0 through end points 3 and 4, respectively), the difference between the average returns of stocks registering a 10 and the average returns of stocks registering a 1 was statistically significant with t-stat of 2.402 and 2.462 and p-values of 0.016 and 0.015, respectively. Time intervals in the table are the end points of each time interval.

* Significant at the 5% level

### Figure 22: Data Set II, Outperformance of 10s; Underperformance of 1s

| Time Interval | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| VBI: 10 | 5.02% | 14.43% | 35.57% | 46.18% |
| VBI: 1 | 2.02% | 4.85% | 13.07% | 21.55% |
| Difference (10 less 1) | 3.0pt | 9.6pt | 22.5pt* | 24.6pt |
| Average Return (Universe) | 4.5% | 10.86% | 19.28% | 29.17% |
| Difference (10 less average) | 0.5pt | 3.6pt | 16.3pt | 17.0pt |
| Difference (1 less average) | -2.5pt | -6.0pt | -6.2pt | -7.6pt |

*Notes:* This figure shows the average returns of stocks registering a 10 and the average returns of stocks registering a 1 in Data Set II over relevant future periods. At time interval 3 (as measured from time 0 through end point 3), the difference between the average returns of stocks registering a 10 and the average returns of stocks registering a 1 was statistically significant with t-stat of 1.899 and p-value of 0.041. Time intervals in the table are the end points of each time interval.

* Significant at the 5% level

### Figure 23: Data Set I, Outperformance of 9-10s; Underperformance of 1-2s

| Time Interval | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| VBI: 9-10 | 4.79% | 7.9% | 19.29% | 23.2% |
| VBI: 1-2 | 2.89% | 7.48% | 13.63% | 17.97% |
| Difference (9-10 less 1-2) | 1.9pt | 0.4pt | 5.7pt | 5.2pt |
| Average Return (Universe) | 3.2% | 7.82% | 14.52% | 18.29% |
| Difference (9-10 less average) | 1.6pt | 0.1pt | 4.8pt | 4.9pt |
| Difference (1-2 less average) | -0.3pt | -0.3pt | -0.9pt | -0.3pt |

*Notes:* This figure shows the average returns of stocks registering a 9-10 and the average returns of stocks registering a 1-2 in Data Set I over relevant future periods. For example, the return of 23.2% is calculated by taking the average of the average return of stocks registering a 9 and the average return of stocks registering a 10 from time 0 through end point 4. Time intervals in the table are the end points of each time interval.

**Figure 24: Data Set II, Outperformance of 9-10s; Underperformance of 1-2s**

| Time Interval | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| VBI: 9-10 | 6.17% | 13.25% | 25.99% | 34.79% |
| VBI: 1-2 | 2.58% | 8.69% | 18.06% | 26.02% |
| Difference (9-10 less 1-2) | 3.6pt | 4.6pt | 7.9pt | 8.8pt |
| | | | | |
| Average Return (Universe) | 4.5% | 10.86% | 19.28% | 29.17% |
| | | | | |
| Difference (9-10 less average) | 1.7pt | 2.4pt | 6.7pt | 5.6pt |
| Difference (1-2 less average) | -1.9pt | -2.2pt | -1.2pt | -3.1pt |

*Notes:* This figure shows the average returns of stocks registering a 9-10 and the average returns of stocks registering a 1-2 in Data Set II over relevant future periods. For example, the return of 34.79% is derived by taking the average of the average return of stocks registering a 9 and the average return of stocks registering a 10 from time 0 through end point 4. Time intervals in the table are the end points of each time interval.

There are a few items worth noting in the tables, the first with respect to cohort construction. When presenting the data for a cohort, “VBI: 9-10” for example, the average return of stocks with Valuentum Buying Index ratings of 9 are averaged with the average return of stocks with Valuentum Buying Index ratings of 10. Said differently, the 13.25% measure for “VBI: 9-10” in Figure 24 at Time Interval 2 (end point 2) reflects the average return of stocks two time intervals (periods, updates) after registering a 9 (12.06%)--from the time the rating is registered to end point 2--with the average return of stocks two time intervals (periods, updates) after registering a 10 (14.43%)--from the time the rating is registered to end point 2.

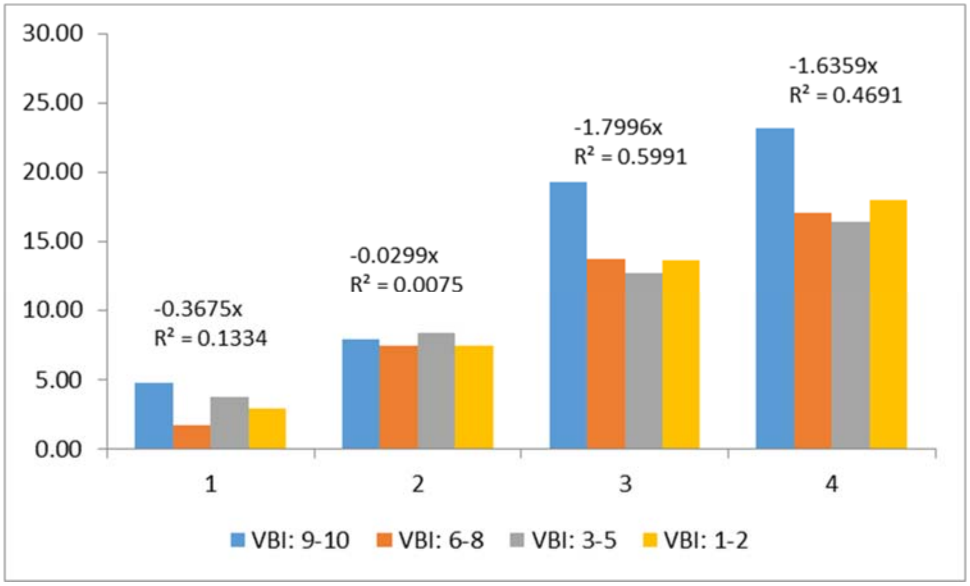
As it relates to the cohort of “VBI: 1-2,” as another example, the average return of stocks with Valuentum Buying Index ratings of 1 are averaged with the average return of stocks with Valuentum Buying Index ratings of 2. Similarly, the 8.69% measure for “VBI: 1-2” in Figure 24 at Time Interval 2 (end point 2) reflects the average return of stocks two time intervals (periods, updates) after registering a 1 (4.85%)--from the time the rating is registered to end point 2--with the average return of stocks two time intervals (periods, updates) after registering a 2 (12.54%)--from the time the rating is registered to end point 2. The “Average Return (Universe)” is calculated by averaging the average return of each rating. All cohorts in this paper are constructed in this manner.

Second, a discussion about how to think about the time interval is required. As shown in Figure 18, the update cycle for a company’s Valuentum Buying Index rating can vary. For example, in the case of Baidu (BIDU), there were 8 updates over the span of 3 years (July 2013 through July 2016), suggesting an average time interval (duration) per Valuentum Buying Index rating update is about 4.5 months or so. In general, we believe the 4.5 month average time interval may be a fair representation across both data sets, but as previously noted, some updates could have been as frequent as one week, and some longer than a half year. Looking at Figures 21-24, we estimate that stocks with the highest Valuentum Buying Index ratings (10) (9-10) outperformed stocks with the lowest Valuentum Buying Index ratings (1) (1-2) over immediate and multiple time intervals (periods, updates), extending to 18 months (4.5 months x 4 time intervals or end points), on average, or 12-24 months, conservatively, on average.

The outperformance of the highest Valuentum Buying Index ratings (9-10) relative to the lowest Valuentum Buying Index ratings (1-2) generally begins to deteriorate around time interval 5 (end point 5), though such a relationship held through time interval 7 (end point 7) in the larger Data Set I. Over longer periods of time, beyond time interval 8 (end point 8), for example, the relationship between the highest Valuentum Buying Index ratings (9-10) and the lowest Valuentum Buying Index ratings (1-2) reverses aggressively, and the worst performance of "9-10 minus 1-2" occurred more than 10 time intervals (approximately 4 years) after the recorded ratings. This may not be surprising, however, as one might expect the greatest relative outperformance of the highest-rated issues relative to the lowest-rated issues to occur over the near term for a number of reasons.

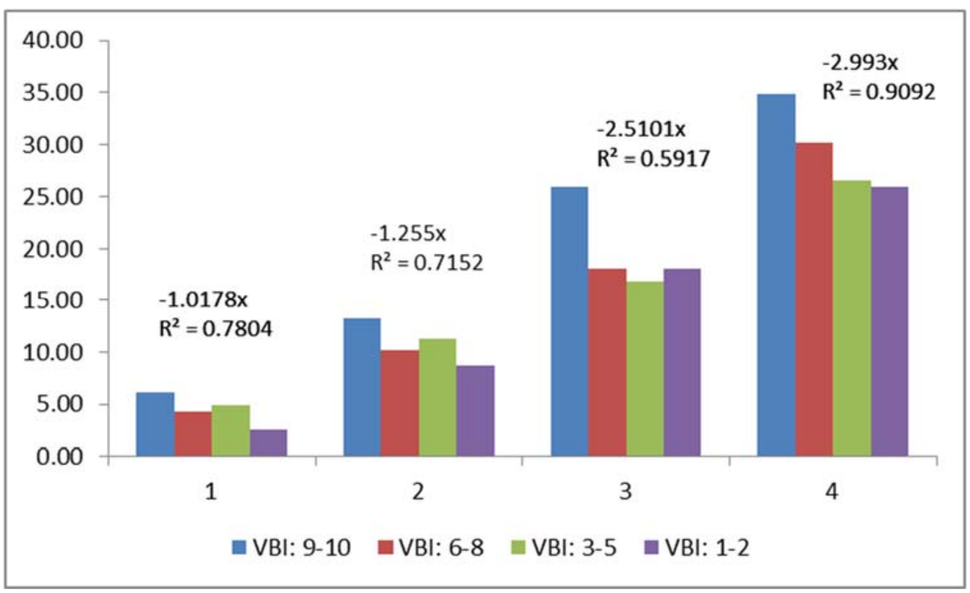
First, Valuentum Buying Index ratings will inevitably change over time, some of them meaningfully and over relatively short periods of time. Rating transition matrices would reveal instances where stocks once rated 1, for example, were rated much higher (5, 6) just a few time intervals (end points) later (e.g. ULTA, TDC, LRN, NPO, SNHY, LANC, etc.). Second, given the market environment of 2011 to mid-2017, it can be argued that some of the most overvalued stocks (generally lower rated) over the duration of the study became even more overvalued (higher priced), perhaps a reflection of increasing risk-seeking behavior by investors through the course of the study period. Third, such near-term outperformance relative to the long term may speak of a timing factor more than factor cyclicality or eroding factor-return outperformance given that Valuentum Buying Index ratings in the times series study have been adjusted/controlled via time intervals (rightsized via time series), striving to make the study independent of market cycles or economic cycles.

**Figure 25: Data Set I, Stock Returns By Valuentum Buying Index Rating Cohort**




*Notes:* This figure reveals negative slope coefficients and the R-squared measures for Valuentum Buying Index ratings in Data Set I grouped by cohort (9-10; 6-8; 3-5; 1-2) over relevant future periods. For example, the return distribution at end point 4 is derived by taking the average of the average return of stocks of each individual rating that form each cohort from time 0 through end point 4. Time intervals in the graph are the end points of each time interval.

**Figure 26: Data Set II, Stock Returns By Valuentum Buying Index Rating Cohort**




*Notes:* This figure reveals negative slope coefficients and the R-squared measures for Valuentum Buying Index ratings in Data Set II grouped by cohort (9-10; 6-8; 3-5; 1-2) over relevant future periods. For example, the return distribution at end point 4 is derived by taking the average of the average return of stocks of each individual rating that form each cohort from time 0 through end point 4. Time intervals in the graph are the end points of each time interval.

Due mostly to the presence of strong performance from stocks registering the highest Valuentum Buying Index ratings, the slope coefficients of the return distributions over Time Intervals 1-4 (end points 1-4) in Figure 25 (Data Set I) are negative, suggesting a degree of sorting efficacy, though R-squared values reveal a less-predictive methodology across various cohorts than the return distributions of those in Figure 26 (Data Set II). We attribute the low R-squared values in Figure 25 (Data Set I) to "behavior" in cohorts that contain Valuentum Buying Index ratings of 8 and 2 (perhaps in stocks that may have been "mis-ranked"), a topic that we discuss in greater detail because of its significance to the presence of a value-timing factor and ultra-momentum factor, respectively.

The more negative slope coefficients and higher R-squared values in Data Set II reflect generally better "behavior" by the underlying average ratings comprising such cohorts. The strongest ranking tendencies of the Valuentum Buying Index ratings appear to occur through time intervals (periods, updates) 3-4, or 13.5-18 months subsequent to the published Valuentum Buying Index rating, and then tend to lose their sorting efficacy increasingly beyond that point, reasons for which discussed previously. On the basis of the construction and design of the Valuentum Buying Index, we'd expect the rating system to have a less-strong signal in the "big middle," where ratings can have contradicting expected near-term return profiles, and the time series study seems to support this.

*Time Series Study -- The value-timing factor*

The time series study of Valuentum Buying Index offers a unique lens into the performance of a cohort of undervalued stocks with varying characteristics. Stocks that are undervalued on both an enterprise free cash flow and on a relative valuation basis and have good technical/momentum characteristics, or both good value and good momentum factors within them, are assigned a Valuentum Buying Index rating of 9. Stocks that have such characteristics but also other compensated factors--namely quality, but also perhaps value-creating growth and manageable leverage--are assigned the highest rating of 10, while stocks that are undervalued on both an enterprise free cash flow and on a relative valuation basis but have neutral technical/momentum characteristics receive a rating of 8 (Nelson 2011).

Stocks that are undervalued on both an enterprise free cash flow basis and relative value basis but have poor technical/momentum indicators are rated 6, but because such stocks are grouped with other stocks rated 6 that have various other value and technical/momentum combinations, the time series corresponding to such 6-rated stocks is not easily discernable within the data sets, and therefore not included in the value-timing factor analysis. By using Valuentum Buying Index data for ratings of 8, 9 and 10, however, we are still able to control for the value factor and explicitly assess a timing consideration. To test the presence of a value-timing factor within the Valuentum Buying Index rating system, we compare the average return performance of 9-10s with the return performance of 8s across both data sets over near-term time intervals (end points).

**Figure 27: Data Set I, Value-timing Factor in Undervalued Stocks**

| Time Interval | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| VBI: 9-10 | 4.79% | 7.9% | 19.29% | 23.2% | 21.6% |
| VBI: 8 | -3.67% | 4.01% | 15.32% | 18.57% | 8.86% |
| Difference (9-10 less 8) | 8.46pt | 3.89pt | 3.97pt | 4.63pt | 12.74pt |

*Notes:* This figure shows the average of the average returns of stocks registering a 9 and 10 and the average returns of stocks registering an 8 in Data Set I over relevant future periods. At time interval 1 (as measured from time 0 through end point 1), the difference between the average of the average returns of stocks registering a 9 and 10 and the average returns of stocks registering an 8 generated a t-stat of 1.683 and p-value of 0.052. Time intervals in the table are the end points of each time interval.

**Figure 28: Data Set II, Value-timing Factor in Undervalued Stocks**

| Time Interval | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| VBI: 9-10 | 6.17% | 13.25% | 25.99% | 34.79% | 30.94% | 44.94% |
| VBI: 8 | 2.01% | 10.38% | 19.8% | 41.33% | 29.35% | 26.46% |
| Difference (9-10 less 8) | 4.15pt | 2.87pt | 6.19pt | -6.54pt | 1.59pt | 18.48pt |

*Notes:* This figure shows the average of the average returns of stocks registering a 9 and 10 and the average returns of stocks registering an 8 in Data Set II over relevant future periods. For example, the return of 44.94% is derived by taking the average of the average return of stocks registering a 9 and the average return of stocks registering a 10 from time 0 through end point 4. Time intervals in the table are the end points of each time interval.

In both Data Set I and Data Set II, the Valuentum Buying Index reveals a tendency to sort equities within an identified cohort of undervalued stocks on the basis of their relative timeliness. For example, stocks that generated ratings of 9-10 tended to outperformed stocks that generated ratings of 8 immediately, on average and over sustained periods of time. Interestingly, one of the only negative average returns (-3.67%) across any individual rating over any time interval occurred at Time Interval 1 (end point 1) with respect to a Valuentum Buying Index rating of 8 (see Figure 27), suggesting that by sorting undervalued stocks (i.e. categorizing them between 9-10 and 8, respectively), the Valuentum Buying Index identified those stocks within a subset of undervalued equities as potentially the most timely to consider (i.e. 9-10 versus 8) within the study.

The negative average return for a rating of 8 in Time Interval 1 (end point 1) is unique given that, prior to study results, the hypothesized near-term expected return for the rating was expected to be poor relative to other undervalued equities and that stocks with such a rating arguably fit the hypothesized profile of “value traps.” Excluding the negative return of the Valuentum Buying Index rating of 8 from the return distribution in Figure 25 (Data Set I), the R-squared value for Time Interval 1 (end point 1) improves to 0.96, though subsequent R-squared measures in that data set are not substantially enhanced from the exclusion. Excluding the return of the

Valuentum Buying Index rating of 8 in Figure 26 (Data Set II), or 2.01%, the lowest generated return of any rating in that time interval with respect to that data set, the R-squared value or Time Interval 1 (end point 1) improves to 0.89, though subsequent R-squared measures in that data set are reduced from the exclusion.

*Time Series Study – The ultra-momentum factor*

In the time series study, we may have witnessed the presence of an ultra-momentum factor, a condition we hypothesize is generally most prevalent during lengthy stock market advances (as in the period that covers the time series study). Stocks rated 1 and 2 on the Valuentum Buying Index are assessed to be overvalued on both an enterprise free cash flow basis and a relative value basis, but stocks rated 2 are assessed to have comparatively better technical/momentum indicators than stocks rated 1 (neutral versus "bearish," respectively). Stocks that are overvalued on both an enterprise free cash flow basis and relative value basis but have "bullish" (good) technical/momentum indicators are rated 4, but because such stocks are grouped with other stocks rated 4 that have various other value and technical/momentum combinations, the time series corresponding to such 4-rated stocks is not easily discernable within the data sets, and therefore not included in the ultra-momentum factor analysis. By using Valuentum Buying Index data for ratings of 1 and 2, however, we are still able to control for the value factor (overvalued in this case) and explicitly assess an ultra-momentum consideration.

To test the presence of an ultra-momentum factor within the Valuentum Buying Index rating system, we compare the return performance of 2s with the return performance of 1s across both data sets over time intervals (periods, updates). In the same manner that we would expect stocks that are rated 9 and 10 on the Valuentum Buying Index to outperform VBI-rated 8 stocks in sorting timeliness within a cohort of undervalued stocks, we would expect VBI-rated 2 stocks to generally outperform VBI-rated 1 stocks in identifying momentum within a cohort of overvalued stocks. Across both data sets, the average return of stocks rated 2 was significantly higher than the average return of stocks rated 1 over immediate and multiple time intervals (periods, updates). In Data Set II, for example, outperformance of VBI-rated 2 equities was sustained through Time Interval 5 (end point 5), while in Data Set I outperformance never ceased but only grew through Time Interval 13 (end point 13), unique "behavior" that we call ultra-momentum.

**Figure 29: Sorting Ultra-Momentum in Overvalued Stocks**

| Time Interval | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| Data Set I: (2 less 1) | 1.12pt | 5.11pt | 7.60pt | 17.23pt * | 12.67pt |
| Data Set II: (2 less 1) | 1.12pt | 7.70pt | 9.99pt | 8.93pt | 10.79pt |

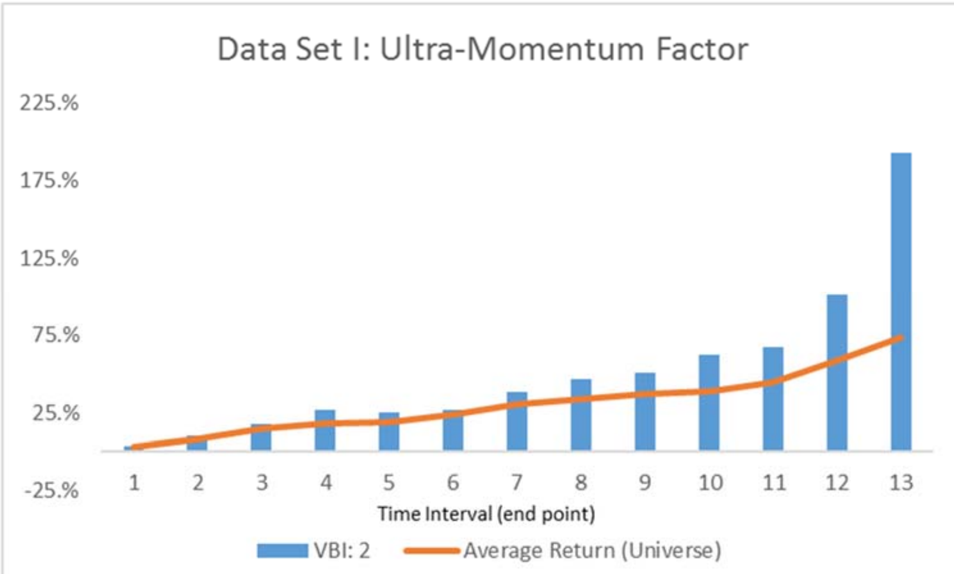
*Notes:* This figure shows the difference in the average returns between stocks with Valuentum Buying Index ratings of 2 and stocks with Valuentum Buying Index ratings of 1 in both Data Sets I and II over relevant future periods. In Data Set I, at time interval 4 (as measured from time 0 through end point 4), the difference between the average returns of stocks registering a 2 and the average returns of stocks registering a 1 was statistically significant with t-stat of 2.179 and p-value of 0.021. In Data Set II, at time interval 3 (as measured from time 0 through end point 3), the difference between the average returns of stocks registering a 2 and the average returns of stocks registering a 1 generated a t-stat of 1.536 and p-value of 0.073. Time intervals in the table are the end points of each time interval.

* Significant at the 5% level

In sorting returns of stocks rated 2 versus stocks rated 1 (i.e. assigning a relatively higher rating to stocks rated 2 than stocks rated 1), the Valuentum Buying Index seems to be identifying what we describe as an ultra-momentum factor within a cohort of overvalued stocks, something we originally hypothesized to be prevalent in overpriced stocks that tend to continue to "run" higher during lengthy stock market advances. In the equity-market environment that covered the duration of the time series study (2011 through mid-2017), it can be reasonably argued that overvalued stocks with good share-price momentum became even more aggressively overvalued, or perhaps equally likely, the Valuentum Buying Index identified stocks rated 2 that we believed were overvalued, but that turned out not to be (given their subsequent strong price returns), effectively optimizing the sorting of "true" overvalued stocks within the system (i.e. differentiating between 1s and 2s).

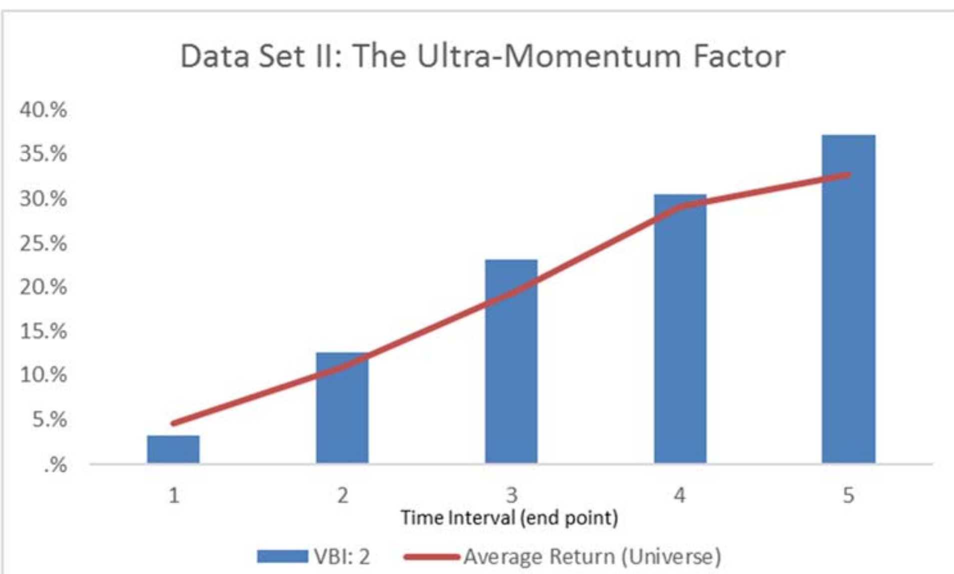
The comparatively higher average returns for stocks rated 2, even with respect to higher-rated issues across most time intervals (periods, updates), is unique given that, prior to study results, the hypothesized expected return for the rating was theorized to be good relative to other overvalued equities and that stocks with such a rating arguably fit the hypothesized profile of "ultra-momentum" stocks, or a cohort of equities less likely to revert to their estimated intrinsic values over the immediate near term. Stocks that contributed to the average return of Time Interval 13 in Data Set I, for example, included Netflix (NFLX), Sherwin Williams (SHW), Crown Castle (CCI), and Hershey Foods (HSY). The duration of the outperformance of ultra-momentum stocks was less pronounced in Data Set II than in Data Set I, but present nonetheless.

**Figure 30: Data Set I, The Outperformance of Ultra-Momentum Stocks**




*Notes:* This figure shows the average return of stocks registering a Valuentum Buying Index rating of 2 and the average of the average returns corresponding to stocks of each Valuentum Buying Index rating in Data Set I. Time intervals in the chart are the end points of each time interval.

**Figure 31: Data Set II, The Outperformance of Ultra-Momentum Stocks**

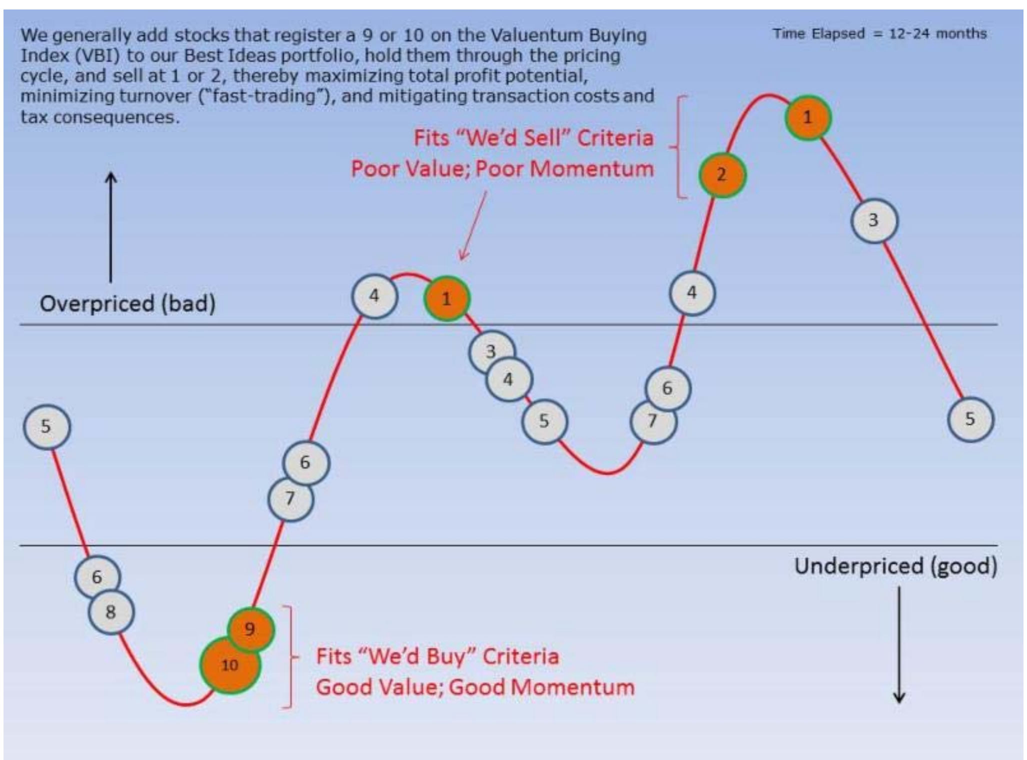



*Notes:* This figure shows the average return of stocks registering a Valuentum Buying Index rating of 2 and the average of the average returns corresponding to stocks of each Valuentum Buying Index rating in Data Set II. Time intervals in the chart are the end points of each time interval.

*Time Series Study – The unique significance of 8s and 2s*

As shown below in Figure 32 (circa early 2015), a theoretical illustration of when Valuentum Buying Index ratings may occur during hypothetical stock pricing cycles, the rating of 8, for example, generally occurs in a *single instance* when immediate, one-directional negative returns are expected. In the time series study, the average return of stocks with a rating of 8 was revealed to have the lowest return of any rating during Time Interval 1 (end point 1), and one that was even negative in Data Set I. The rating of 2, on the other hand, generally occurs in a *single instance* when immediate, one-directional positive returns are expected, and in the time series study, the average return of stocks with a rating of 2, despite being embedded in a cohort of overvalued stocks, was revealed to have among the better returns over near-term time intervals (periods, updates). The illustration also shows the ambiguity of "big middle" ratings, where a Valuentum Buying Index rating could potentially have contradicting expected trajectories over the near term (e.g. 4, 6), and how multiple scenarios for stocks to earn 3 and 7 could complicate their respective near-term return profile rankings (see also Figure 1 where ratings 3 and 7 have three potential paths).

**Figure 32: Illustration of When Valuentum Buying Index Ratings May Occur**

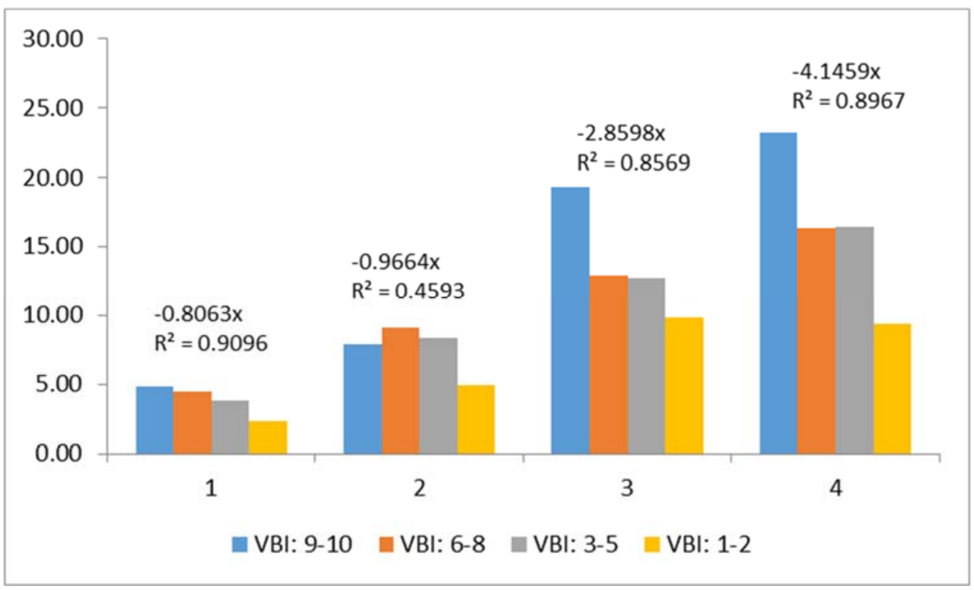



*Notes:* This figure shows when Valuentum Buying Index ratings may occur during a hypothetical pricing cycle. Image shown for illustration purposes only.

As we continue to optimize the Valuentum Buying Index rating system, we may look to adjust what appears to be a potential "over-rating" of stocks that register an 8 ("value-traps") and a potential "under-rating" of stocks that register a 2 ("ultra-momentum"). As designed, the Valuentum Buying Index appears to be effectively identifying "value traps," labeling them as 8-rated stocks, but the rating itself as an 8 may not be punitive (low) enough compared to other ratings to be reflective of, or accurately capture (rank), such a view. Similarly, the Valuentum Buying Index appears to be effectively identifying an "ultra-momentum" factor, labeling it as 2-rated stocks, but the rating itself as a 2 may not be good (high) enough compared to other ratings to be reflective of, or accurately, capture (rank), such a view. In Figures 33 and 34, we reveal the improved sorting efficacy (more negative slope coefficients and generally higher R-squared measures) of the Valuentum Buying Index rating system when 8s and 2s are omitted from the return distributions.

**Figure 33: Data Set I, Stock Returns By Adjusted Valuentum Buying Index Rating Cohort**

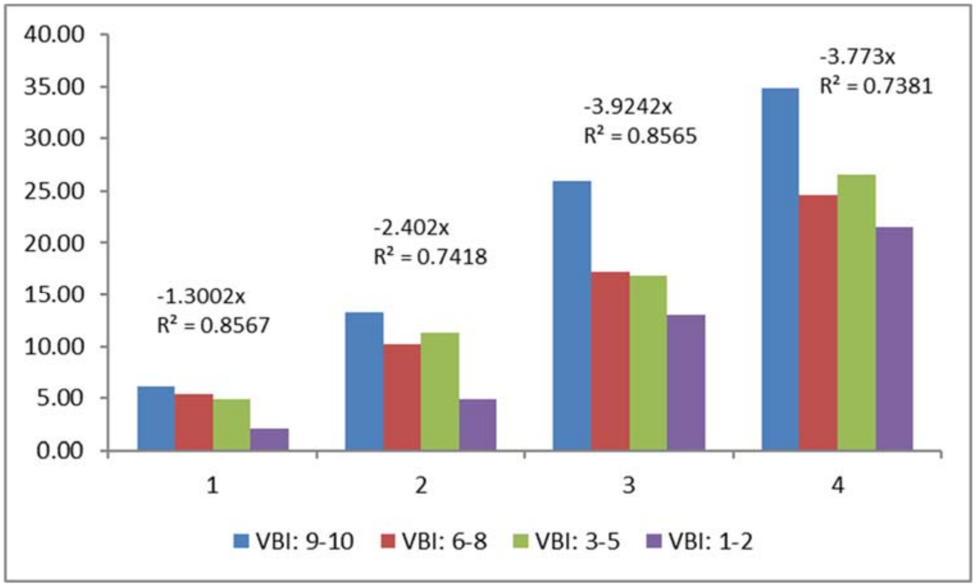
*The following return distributions omit returns from ratings 8 and 2.*




*Notes:* This figure reveals generally improved negative slope coefficients and higher R-squared measures for Valuentum Buying Index ratings in Data Set I grouped by cohort (9-10; 6-8; 3-5; 1-2) over relevant future periods, after omitting the average returns of ratings 8 and 2 in the distributions. The return distribution at end point 4, for example, is derived by taking the average of the average return of stocks of each individual rating, excluding ratings 8 and 2, that form each cohort from time 0 through end point 4. Time intervals in the graph are the end points of each time interval.

**Figure 34: Data Set II, Stock Returns By Adjusted Valuentum Buying Index Rating Cohort**

*The following return distributions omit returns from ratings 8 and 2.*




*Notes:* This figure reveals generally improved negative slope coefficients and the R-squared measures for Valuentum Buying Index ratings in Data Set II grouped by cohort (9-10; 6-8; 3-5; 1-2) over relevant future periods, after omitting the average returns of ratings 8 and 2 in the distributions. The return distribution at end point 4, for example, is derived by taking the average of the average return of stocks of each individual rating, excluding ratings 8 and 2, that form each cohort from time 0 through end point 4. Time intervals in the graph are the end points of each time interval.

*Time Series Study – Overlapping relevant, unique and compensated factors*

The presence of additional relevant, unique and compensated factors may have been evident in the time series study, as revealed by the performance of VBI-rated 10 equities relative to VBI-rated 9 equities. For example, stocks registering a 10 on the Valuentum Buying Index are generally of incremental better quality, have higher growth (i.e. value-creating growth), and/or have better leverage metrics than stocks registering a 9 on the Valuentum Buying Index, the latter rating of 9 itself a very tall order for any stock. Cash flow generation and relative pricing strength were other criteria that differentiated VBI-rated 10 equities from VBI-rated 9 equities. The relative outperformance of stocks registering a 10 on the Valuentum Buying Index relative to 9 (and 8) was also generally apparent over near-term time intervals (periods, updates).

**Figure 35: Data Set I, Outperformance of 10s Relative to 9s and 8s**

| Time Interval | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| VBI: 10 | 6.55% | 11.52% | 28.9% | 28.59% |
| VBI: 9 | 3.04% | 4.28% | 9.68% | 17.81% |
| VBI: 8 | -3.67% | 4.01% | 15.32% | 18.57% |
| Difference (10 less 9) | 3.51pt | 7.25pt | 19.22pt | 10.78pt |
| Difference (10 less 8) | 10.22pt | 7.51pt | 13.58pt | 10.02pt |

*Notes:* This figure shows the average returns of stocks registering a 10 and the average returns of stocks registering a 9 and 8, respectively, in Data Set I over relevant future periods. At time interval 3 (as measured from time 0 through end point 3), the difference between the average returns of stocks registering a 10 and the average returns of stocks registering a 9 generated a t-stat of 1.674 and p-value of 0.059. Time intervals in the table are the end points of each time interval.

**Figure 36: Data Set II, Outperformance of 10s Relative to 9s and 8s**

| Time Interval | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| VBI: 10 | 5.02% | 14.43% | 35.57% | 46.18% | 34.71% | 56.31% |
| VBI: 9 | 7.31% | 12.06% | 16.41% | 23.4% | 27.16% | 33.57% |
| VBI: 8 | 2.01% | 10.38% | 19.8% | 41.33% | 29.35% | 26.46% |
| Difference (10 less 9) | -2.29pt | 2.37pt | 19.16pt * | 22.78pt | 7.55pt | 22.74pt |
| Difference (10 less 8) | 3.01pt | 4.05pt | 15.78pt | 4.85pt | 5.37pt | 29.85pt |

*Notes:* This figure shows the average returns of stocks registering a 10 and the average returns of stocks registering a 9 and 8, respectively, in Data Set II over relevant future periods. At time interval 3 (as measured from time 0 through end point 3), the difference between the average returns of stocks registering a 10 and the average returns of stocks registering a 9 was statistically significant with a t-stat of 1.851 and p-value of 0.043. Time intervals in the table are the end points of each time interval.

* Significant at the 5% level

*Conclusions*

This work extends the theory of the "The Arithmetic of Active Management" to the investor level. The recent popularity of indexing has been supported in part by widely-disseminated syllogisms in scholarly works far and wide, and we strive to advance such syllogisms via hypothetical example, extending them to the investor level. We also develop and present a new syllogism of the stock market, which readers may find as equally compelling as those developed by Sharpe and Bogle in the past.

The paper addresses certain data problems of factor-based methods, namely with respect to value and book-to-market ratios. We provide by example how very important companies such as Boeing (BA), a component of the Dow Jones Industrial Average, for example, can have negative accounting book value and may be excluded in part or in whole from academic studies. We raise the issue of the possibility that academic studies utilizing multiple analysis within the context of a value factor may not be precisely measuring what they think they may be measuring.

A more controversial topic, the work may lay the foundation for academic literature regarding the Valuentum, the value-timing, and ultra-momentum factors. We showcase the performance of a fundamentally-based, multi-factor methodology that includes price-to-fair value ratios, or measures of the difference between price and value. We think using price-to-fair value ratios in measuring a value factor may be a solution to the issue raised with respect to the application of multiples (e.g. book-to-market ratios, price-to-earnings ratios) within factor-based value approaches, an important consideration from a practitioner's point of view.

The case for the Valuentum factor, the Valuentum Buying Index, or the Valuentum Style of Investing remains an excellent one, in our view. The Valuentum Buying Index effectively sorted "winners" and "losers" in both the case-study and time-series studies, where average returns from the highest Valuentum Buying Index ratings (10) (9-10) significantly outperformed average returns from the lowest Valuentum Buying Index ratings (1) (1-2) over immediate multiple time intervals (periods, updates). Negative slope coefficients across Valuentum Buying Index rating cohorts speak to a generalized tendency of higher Valuentum Buying Index ratings outperforming lower Valuentum Buying Index ratings, though varying R-squared values suggest the signal is less-strong in the "big middle" (3-8), as expected and as designed (given the potential for contradicting expected near-term return profiles for certain ratings).

In the time series study, the Valuentum Buying Index revealed the ability to sort undervalued stocks on the basis of their respective timeliness (9-10 less 8), showcasing the system's potential usefulness as a value-timing indicator in avoiding "value traps." The Valuentum Buying Index successfully sorted overvalued stocks on the basis of relative momentum (2 less 1), revealing the presence of what we describe to be an "ultra-momentum" factor, which we believe was augmented by the market conditions of the time-series study period. The outperformance of VBI-rated 10 issues relative to the rest of the universe of stocks (including VBI-rated 9 equities) supports the view that an increasing overlap of relevant, unique and compensated factors *within individual stocks*, even beyond those of value and technical/momentum--namely quality and perhaps value-creating growth and manageable leverage as in 10-rated VBI issues--may be one of the most important drivers behind individual stock outperformance.

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**Appendix – Data (time series study)**

Valuentum records its own Valuentum Buying Index ratings, share-price data (from Xignite), and corresponding fair value estimate data. In the time series study, our best efforts were applied to adjust share-price data for material stock splits/one-time dividends during the duration of each company's share-price time series. Share-price time series were adjusted for stock splits of 1.2:1 or greater, but generally not adjusted for companies engaging in frequent, small stock dividends or small stock splits over the period of study (e.g. ATRO). Share-price time series identified to have been impacted by reverse stock splits were also adjusted (e.g. MNI, CDTI, BEBE), and share-price time series of companies that were identified to have engaged in large, material one-time dividends were also adjusted (e.g. SYNT). Several companies' pricing time series that seemed to have already been adjusted for announced stock splits, including reverse stock splits, within the data set were not further adjusted (e.g. DF, MT, MUR).

Several companies engaged in business separations that impacted their share price time series during the study. Where both separated companies were then covered by Valuentum's stock research, each respective share-price time series was combined (e.g. EBAY/PYPL; ABT/ABBV) with pricing information at the time of future periodic updates (there may exist price/time discrepancies under such a method, but any will be immaterial to the study). Where both separated companies were then not covered by Valuentum's stock research, share-price time series were combined by adding pricing data of the spin-off at the time of future updates of the covered company to the pricing data of the covered company at the time of future updates (e.g. ENR/EPC), or when pricing data was not readily available, pricing data for the spin-off at time of spin-off, was applied to the covered company's future price uniformly at the time of future updates (e.g. NI/CPGX).

Return data corresponding to each respective Valuentum Buying Index rating generally does not aim to or reflect the proportion of returns attributed to the payment of dividends. Because the generation of a fair value estimate via an enterprise free cash flow approach is generally independent of dividend policy, Valuentum Buying Index ratings, which utilize enterprise-free-cash-flow-derived fair value estimates, are also generally independent of dividend policy, and as such, the dividend and therefore the timing of the payment of the dividend are excluded and believed to be inconsequential to the conclusions of this study. We believe dividends should generally be randomly dispersed across Valuentum Buying Index ratings and any respective cohorts and such ratings, and if not, efforts would have been made to adjust the data for dividends to isolate the impact of the Valuentum Buying Index rating on future expected share-price returns.

*This study discusses backtested and/or "walk-forward" information regarding the Valuentum Buying Index. The Best Ideas Newsletter portfolio and Dividend Growth Newsletter portfolio are not real money portfolios. Actual results with respect to the Valuentum Buying Index or Valuentum's newsletter portfolios may differ from simulated information, results, or performance presented. All results are hypothetical and do not represent actual trading. Hypothetical results are intended for illustrative purposes only. There is risk of substantial loss associated with investing in financial instruments.*

## Our Stock Selection Methodology

## The Valuentum Buying Index

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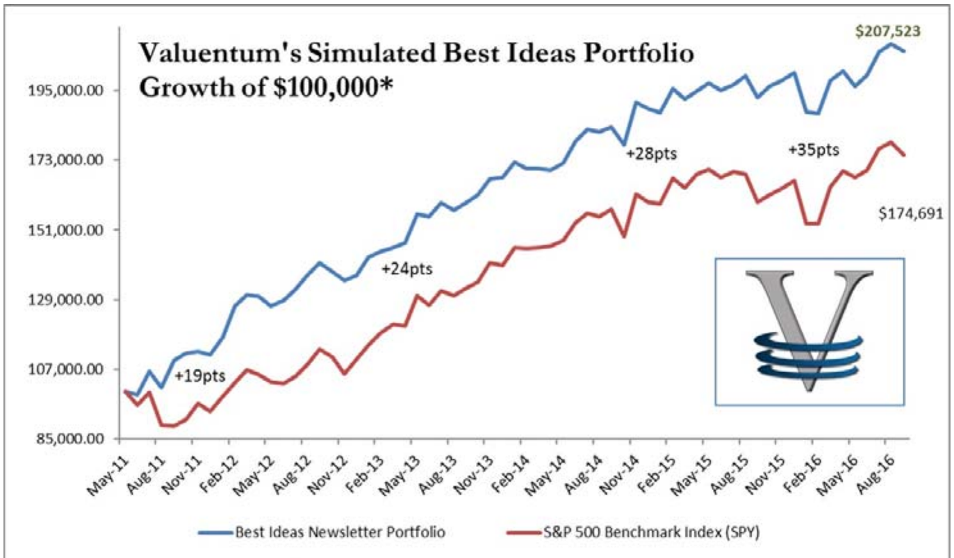
# Our Stock-Selection Methodology, the Valuentum Buying Index

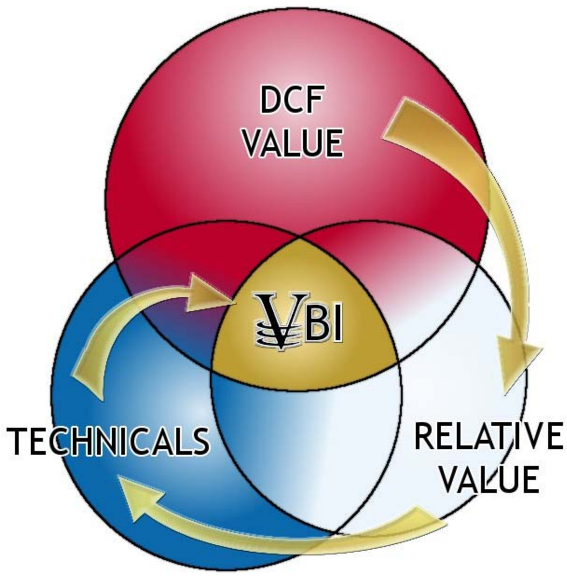
### Our Methodology for Selecting Stocks -- the Valuentum Buying Index

At Valuentum, we think some of the best opportunities arise from an understanding of a variety of investing disciplines in order to identify the most attractive stocks at any given time. Valuentum therefore analyzes each stock across a wide spectrum of philosophies, from deep value through momentum investing. We think companies that are attractive from a number of investment perspectives--whether it be growth, value, income, momentum, etc.--have the greatest probability of capital appreciation and relative outperformance. The more deep-pocketed institutional investors that are interested in the stock for reasons based on their respective investment mandates, we posit the more likely it will be bought and the more likely the price will move higher to converge to its “true” intrinsic value (buying a stock pushes  its price higher). On the other hand, we think the worst stocks will be shunned by most investment disciplines and display expensive valuations, poor technicals and deteriorating momentum indicators.




* Performance is hypothetical and does not represent actual trading. Actual results may differ from simulated information being presented.

We think stocks that meet our demanding criteria fall in the center of the Venn diagram below, displaying attractive characteristics from a discounted cash-flow basis, a relative value basis, and with respect to a technical and momentum assessment. The size of the circles generally reveals the relative emphasis we place on each investment consideration, while the arrows display the order of our process -- value first then technicals and momentum last. We may like firms that are undervalued on both on a discounted cash flow (DCF) basis and relative value basis, but we won't like firms just because they're currently exhibiting attractive technical or momentum indicators. We're not traders or speculators. We target the long term, and we want to have a strong process to support the ideas we deliver to our subscribers.

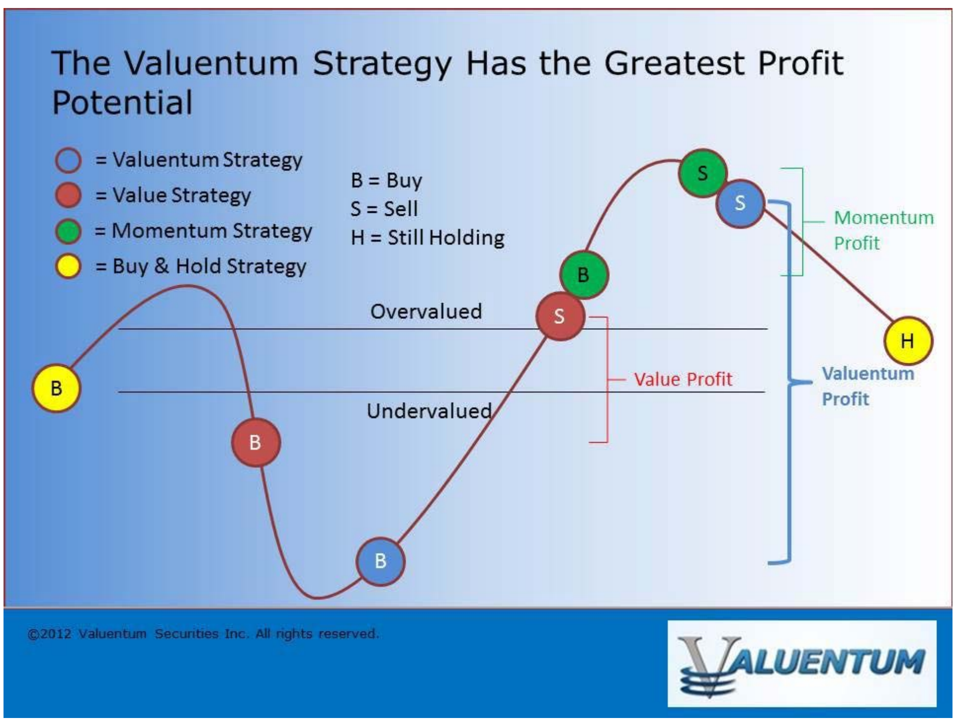



The center of the Venn diagram above, the Valuentum Buying Index (VBI) combines rigorous financial and valuation analysis with an evaluation of a firm's technicals and momentum indicators to derive a rating between 1 and 10 for each company (10=best). Because the process factors in a technical and momentum assessment after evaluating a firm's investment merits via a rigorous DCF and relative-value process, the VBI attempts to identify entry and exit points on what we consider to be the most undervalued stocks.

| VBI Score | Potential Action |
|---|---|
| 10 | Top Pick |
| 9 | We'd Consider Buying |
| 6 to 8 | Constructive (tactical add / trim) |
| 3 to 6 | Less Exciting (tactical add / trim) |
| 1 to 2 | We'd Consider Selling |

We think research firms that just focus on valuation may expose readers to a stock on its way down (a falling knife), while those that just use technical and momentum indicators may expose portfolios to significantly overpriced stocks at their peaks. It is our view that only when both sides of the investment spectrum are combined can investors find undervalued stocks at potentially timely prices for consideration.

Let's examine the chart below, which showcases how the Valuentum process, by definition, may have the greatest profit potential of any common investing strategy. The Valuentum process targets adding stocks to actively-managed portfolios when both value and momentum characteristics are "good" and removing them when both value and momentum characteristics are "bad" (blue circles: Buy --> Sell). We define the Valuentum strategy as capturing the entire equity pricing cycle, while the value and momentum strategies individually truncate profits, as illustrated in the image below.

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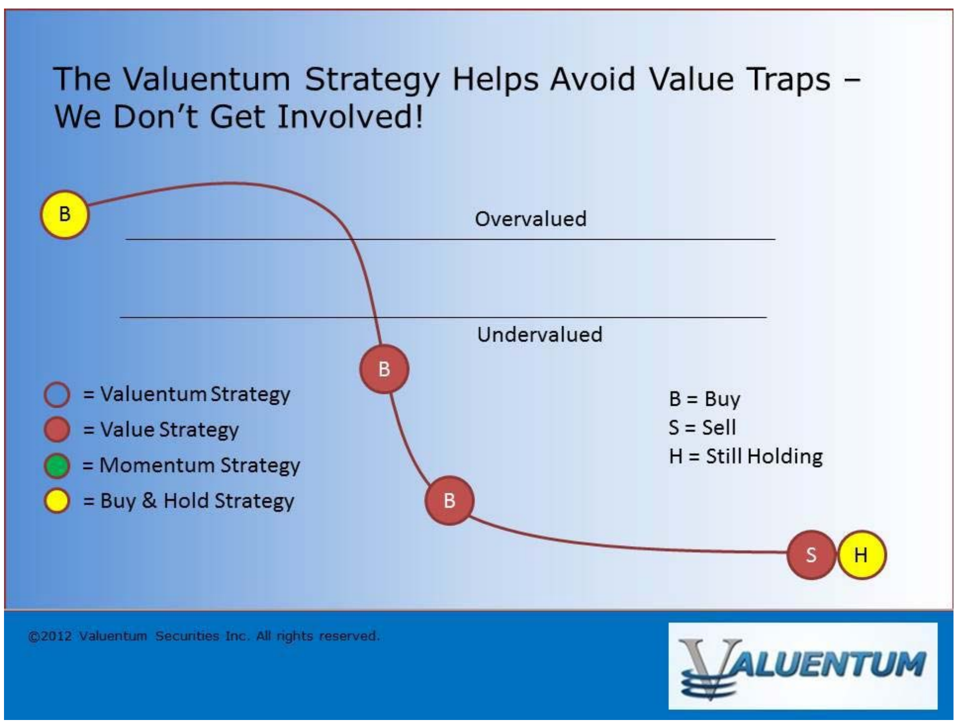
Furthermore, we think Valuentum subscribers are less likely to be involved in so-called value traps because we demand material revenue and earnings growth for firms to earn a 10 on the Valuentum Buying Index. Value traps often occur as a result of secular declines in a firm's products or services, resulting in deteriorating revenue and earnings trends (and often a falling stock price). We also think Valuentum subscribers are less likely to be exposed to these "falling knives" since the process requires firms to not only be undervalued, in our opinion, but also be exhibiting bullish technical and momentum indicators before we would consider adding them to the newsletter portfolios.

Since the stock market is a forward-looking mechanism, price usually leads fundamentals. Without a turnaround in price, the risk that the fundamentals of an undervalued stock have not turned for the positive is higher. Where value strategies may encourage the buying of a stock all the way down regardless of whether fundamentals ever turn (red circles: Buy --> Sell), the Valuentum strategy attempts to steer clear of these situations. The Valuentum Buying Index is designed to wait for technical improvement in the equity, which often precedes fundamental changes at the company.

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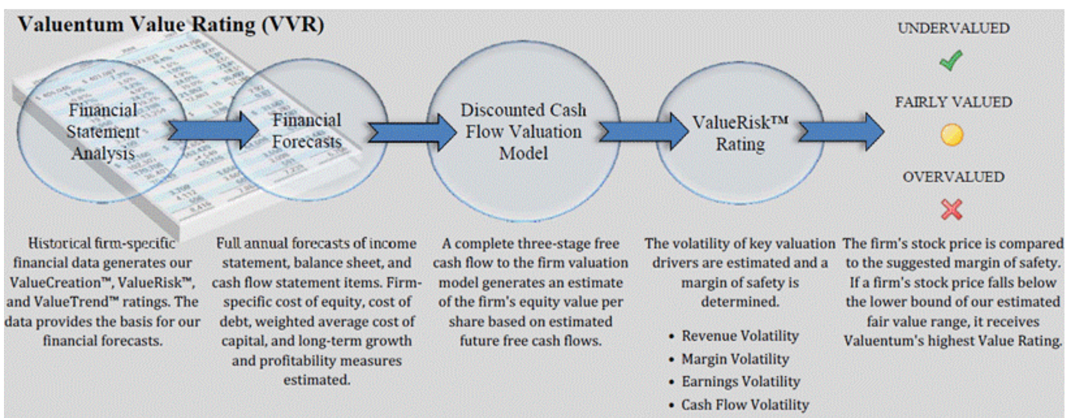
Let's walk through the three investment pillars of our stock-selection methodology.

### I. The Valuentum Buying Index Applies a Rigorous Discounted Cash Flow Valuation Process

The Valuentum Buying Index methodology starts with in-depth financial statement analysis, where we derive our ValueCreation, ValueRisk, and ValueTrend ratings, which together provide a quantitative assessment of the strength of a firm's competitive advantages. We compare a company's return on invested capital (ROIC) to our estimate of its weighted average cost of capital (WACC) to assess whether it is creating economic profit for shareholders (ROIC less WACC equals economic profit). Firms that have improving economic profit spreads over their respective cost of capital score high on our ValueCreation and ValueTrend measures, while firms that have relatively stable returns score well with respect to our ValueRisk evaluation, which impacts our margin-of-safety assessment.

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After evaluating historical trends, we then make full annual forecasts for each item on a company's income statement and balance sheet to arrive at a firm's future free cash flows. We derive a company-specific cost of equity (using a fundamental beta based on the expected uncertainty of key valuation drivers) and a cost of debt (considering the firm's capital structure and synthetic credit spread over the risk-free rate), culminating in our estimate of a company's weighted average cost of capital (WACC). We don't use a market price-derived beta, as we embrace market volatility, which may provide investors with opportunities to buy attractive stocks at bargain-basement levels, in our view. A forward-looking Economic Castle rating is then derived.

We then assess each company within our three-stage free cash flow to the firm (enterprise cash flow) valuation model, which generates an estimate of a company's equity value per share based on its discounted future free cash flows and the company's net balance sheet impact, including other adjustments to equity value (namely pension and OPEB adjustments). Our ValueRisk rating, which considers the underlying uncertainty of the capacity of the firm to continue to generate value for shareholders, sets the margin of safety bands around this fair value estimate. For firms that are trading below the lower bound of our margin of safety band, we consider these companies undervalued based on our DCF process. For firms that are trading above the higher bound of our margin of safety band, we consider these companies overvalued based on our DCF process.

We think a focus on discounted cash-flow (DCF) valuation helps to prevent investors from exposing their portfolios to significantly overpriced stocks at their peaks. The image below reveals how pure momentum investors may expose their portfolios to pricing extremes and dramatic falls (green circles: Buy --> Sell). The Valuentum Buying Index attempts to steer clear of these situations.


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### II. The Valuentum Buying Index Incorporates A Forward-Looking Relative Value Assessment

Our discounted cash-flow process allows us to arrive at an absolute view of the firm's intrinsic value. However, we also understand the critical importance of assessing firms on a relative value basis, versus both their industry and peers. Many institutional money-managers--those that drive stock prices--pay attention to a company's price-to-earnings (PE) ratio and price-earning-to-growth (PEG) ratio in making buy/sell decisions. With this in mind, we have included a forward-looking relative value assessment in our process to further augment our rigorous discounted cash-flow process. If a company is undervalued on both a price-to-earnings ratio and a price-earnings-to-growth (PEG) ratio versus industry peers, we would consider the firm to be attractive from a relative value standpoint.

### III. The Valuentum Buying Index Seeks to Avoid Value Traps, Falling Knives and Opportunity Cost

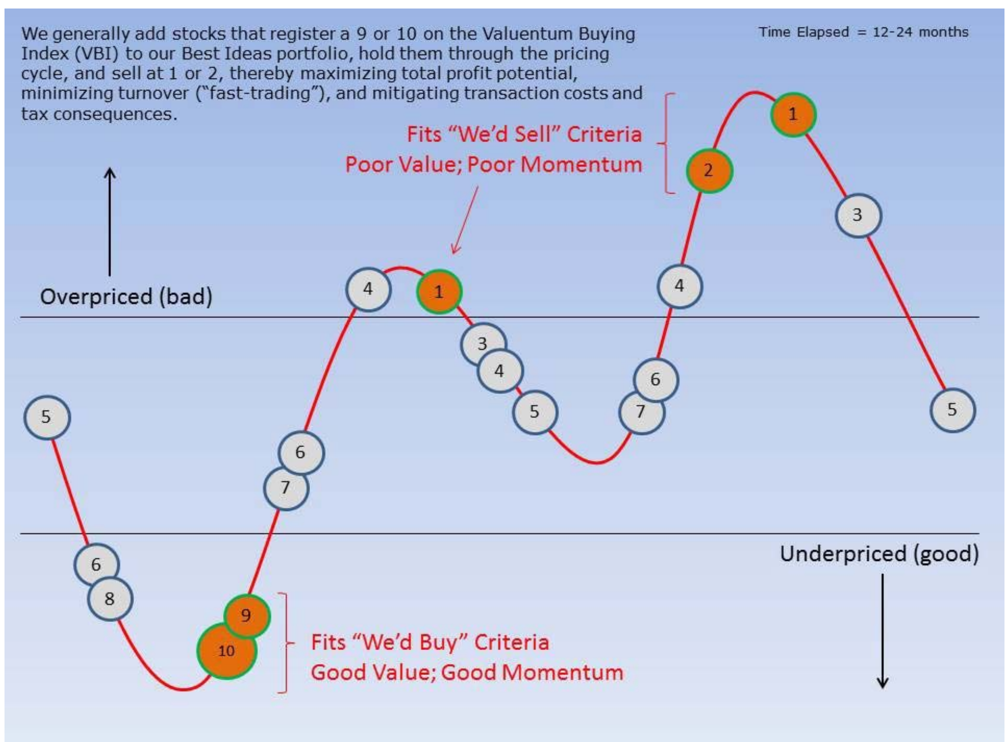
Once we have estimated a firm's intrinsic value on the basis of our discounted cash-flow process, determined if it is undervalued according to its firm-specific margin of safety bands, and assessed whether it has relative value versus industry peers, we then evaluate the company's technical and momentum indicators in an attempt to consider entry and exit points on the stock (but only after it meets our stringent valuation criteria). Rigorous valuation analysis and technical analysis are not mutually exclusive, and we believe both can be used together to bolster idea generation. An evaluation of a stock's moving averages, relative strength, upside-downside volume, and money flow index are but a few considerations we look at with respect to a technical and momentum assessment of a company's stock.

We embrace the idea that the future is inherently unpredictable and that not all fundamental factors can be included in a valuation model. By extension, we use technical and momentum analysis in an attempt to help safeguard against value traps, falling knives, and the opportunity cost of holding an undervalued equity for years before it potentially converges to "fair value." Other research firms may not consider opportunity cost as a legitimate expense for investors.

## Putting It All Together - the Valuentum Buying Index

Though the time frame varies depending on each idea, on a theoretical basis, we would expect our best ideas to "work out" over a 12-24 month time horizon (on average) -- the duration of any individual idea can vary considerably, however. We tend to include firms in the Best Ideas Newsletter portfolio when they register a 9 or 10 on our Valuentum Buying Index (VBI) and tend to remove firms from the Best Ideas Newsletter portfolio when they register a 1 or 2 on the Valuentum Buying Index.

In theory, the Valuentum Buying Index attempts to maximize profits on every idea within the Best Ideas Newsletter portfolio, with the understanding that momentum does exist and that prices over and under shoot intrinsic value all of the time. A value strategy (10 --> 5), for example, may truncate potential profits, while a momentum strategy (4 --> 1), for example, may ignore profits generated via value assessments. The Valuentum Buying Index seeks to capture the entire profit potential, as shown below.

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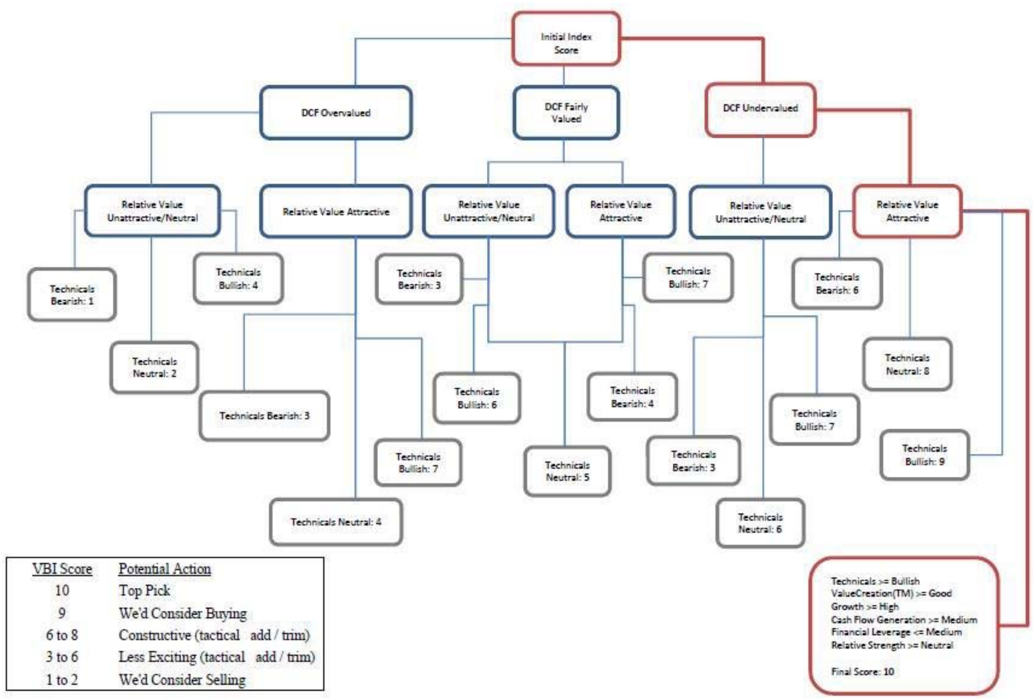
Let's follow the red line on the flow chart below to see how a firm can score a 10, the best mark on the Valuentum Buying Index (a "Top Pick").

First, the company would need to be 'UNDERVALUED' on a DCF basis and 'ATTRACTIVE' on a relative value basis. The stock would also have to be exhibiting 'BULLISH' technicals. The firm would need a ValueCreation rating of 'GOOD' or 'EXCELLENT', exhibit 'HIGH' or 'AGGRESSIVE' growth prospects, and generate at least a 'MEDIUM' or 'NEUTRAL' assessment for cash flow generation, financial leverage, and relative price strength.

This is a tall order for any company. Firms that don't make the cut for a 10 are ranked accordingly, with the least attractive stocks garnering a score of 1 ("We'd sell"). Most of our coverage universe falls between 3 and 7, but at any given time there could be large number of companies garnering either high or low scores, especially at market lows or tops, respectively.

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**How We Use the Valuentum Buying Index in the Best Ideas Newsletter Portfolio**

We often receive questions about how we use the Valuentum Buying Index (VBI) rating system, one of the key metrics we use to source ideas, but we think it is equally important to mention up front that it is only one of the many facets of our website and services. For example, if you haven't checked out the Dividend Cushion ratios on the stocks in your portfolio or the dividend growth product (from individual reports to the newsletter and beyond), surely you are not maximizing your membership! Don't forget about the Economic Castle rating and the Nelson Exclusive publication, too.

No matter your strategy or process though (it is not for us to say what is best for you), the Valuentum Buying Index rating system is still a helpful tool to have at your disposal, even if you are not using it. Admittedly, the VBI, as we call it, is not as easy to evaluate as 1, 2, 3, or even buying 9s and 10s and selling 1s and 2s until their VBI changes upon the next update. Generally speaking, we measure the process over longer-term time periods--from the time a company registers a rating to a defined time in the future--not an interim update basis. Please read more about the parameters of a case study (1) where Valuentum Buying Index ratings, as of September 2013, were recorded and the performance of stocks were measured from that time through September 2014.

**The Valuentum Buying Index Has Checks and Balances**

With prudence and care, the Valuentum Buying Index process and its components are carried out. Our analyst team spends most of its time thinking about the intrinsic value of companies within the context of a discounted cash-flow model and evaluating the risk profile of a company's revenue model. We have checks and balances, too. First, we use a fair value range in our valuation approach as we embrace the very important concept that value is a range and not a point estimate. A relative value overlay as the second pillar helps to add conviction in the discounted cash-flow process, while a technical and momentum overlay seeks to provide confirmation in all of the valuation work. There's a lot happening behind the scenes even before a VBI rating is published, but it will always be just one factor to consider.

Within any process, of course, we value the human, qualitative overlay, which captures a wealth of experience and common sense. We strive to surface our best ideas for members, and flying blind is never a good strategy, in our opinion. In probably one of the most obvious cases, for example, an experienced investor knows when a price-to-earnings (P/E) ratio isn't informative (as in the case of negative or negligible earnings), but a quantitative rating system that uses a P/E ratio may not know any better. That's why the VBI has checks and balances and focuses on the discounted cash-flow process first and foremost, but the human, qualitative overlay is still extremely important, especially when considering various business models and unique "un-modelable" risks. In our opinion, a golf club is only as good as the player that uses it, and in a similar light, a financial model or a rating system is only as good as the user that applies it.

That said, for the sake of transparency, we measure the performance* of the portfolios in the Best Ideas Newsletter and Dividend Growth Newsletter. The portfolios, in part, represent data points measuring the outcome of the work we do on the website, rolled into an assessment: our best ideas for each respective strategy. The ideas in the portfolios in the Best Ideas Newsletter and Dividend Growth Newsletter have been evaluated by our analyst team for consideration in the newsletter portfolios. The thoughts behind the weighting of each idea and the portfolio management process revealed in full transparency on a month to month basis may be worth the cost of a membership alone, even if you're not using the portfolios!

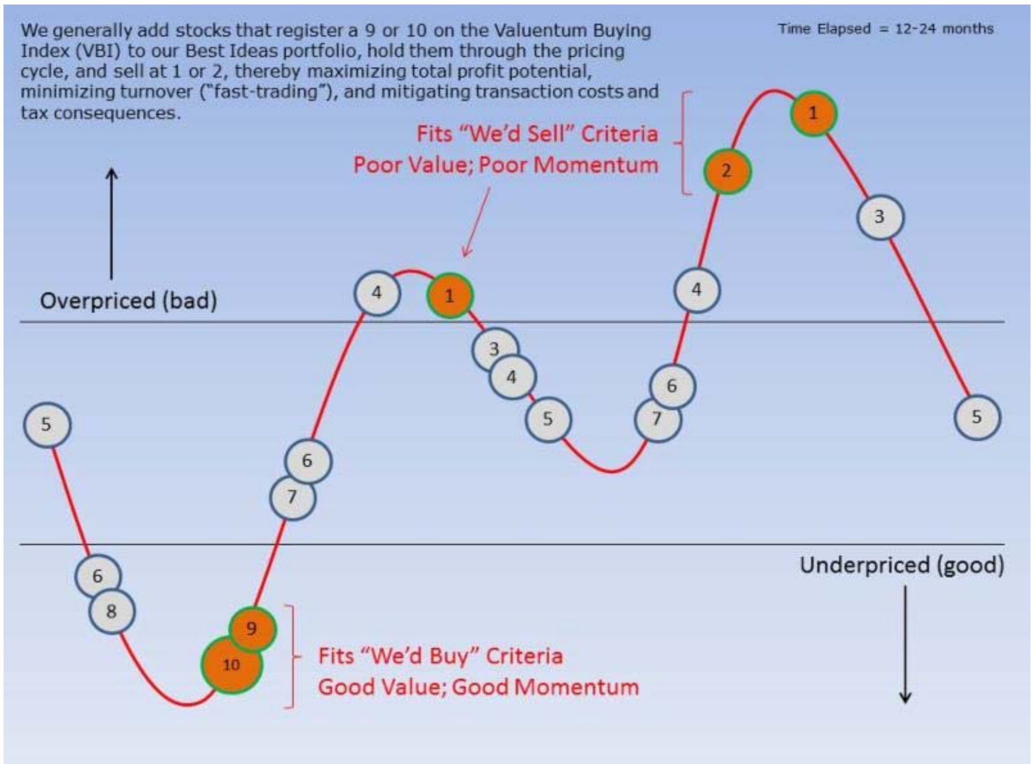
Here's why this is important. In a market environment where more than 90% of large-cap funds have trailed the S&P 500 in the 5-year period ending August 31, 2016, the Best Ideas Newsletter portfolio* has exceeded its benchmark return over a similar time period. What's more, we showcased this performance in full transparency, and we wrote every single day, and some days weren't all that great. When patience may be the secret to success in investing, a lot could have gone wrong with the temptation to do something each day. Obviously, we're very disciplined, but we also credit the portfolio outperformance to the VBI methodology itself. It is a very helpful tool.

** Actual results may differ from simulated information being presented. The Best Ideas Newsletter portfolio and Dividend Growth Newsletter portfolio are not real money portfolios. Results are hypothetical and do not represent actual trading.*

**The Valuentum Buying Index Is One of Many Important Factors to Consider**

That said, let's talk about how the VBI helps to inform which ideas we include in the Best Ideas Newsletter portfolio. This is where some clarification is probably important. For one, the word choice is critical, "inform," because the VBI is generally just one factor that goes into whether we add a company to the Best Ideas Newsletter portfolio, even if the VBI is one of the most important factors. Second, the timing element or duration concept is a key consideration. We've noticed via our statistical backtesting that a momentum factor can be much more pronounced (powerful) over longer periods of time. This was one of the interesting findings of our initial academic white paper study (2012). We try to consider this dynamic with the update cycle of our reports (and the time horizon for ideas to work out). That's why our reports are updated regularly (generally on a quarterly basis) or after material events and not daily or weekly. Perhaps most practically though, we don't think portfolio churn is the way to generate outperformance. Momentum may be high turnover, but Valuentum is low turnover.

Though the time frame varies depending on each idea that we consider for the Best Ideas Newsletter portfolio, we would expect our best ideas to generally work out over a 12-24 month time horizon (on average). Not all ideas will be successful, however. Our “holding period” is targeted to be much, much longer for some ideas in the Dividend Growth Newsletter portfolio, as income and dividend growth are other key factors (in addition to the Valuentum Buying Index and capital appreciation potential). The time horizon or duration concept is where the Valuentum Buying Index rating system becomes more complicated than a simple 1, 2, 3. For example, we tend to "add" stocks to the Best Ideas Newsletter portfolio when they register a 9 or 10 on the Valuentum Buying Index (VBI), "hold" them for some time depending on a number of variables (the VBI, market conditions, sector weightings within the portfolio itself), and then we tend to "remove" stocks from our Best Ideas Newsletter portfolio when they register a 1 or 2 on the VBI. You'll notice that we have a qualitative overlay for the Best Ideas Newsletter portfolio (and one for the Dividend Growth Newsletter portfolio, too, based on dividend-related considerations).

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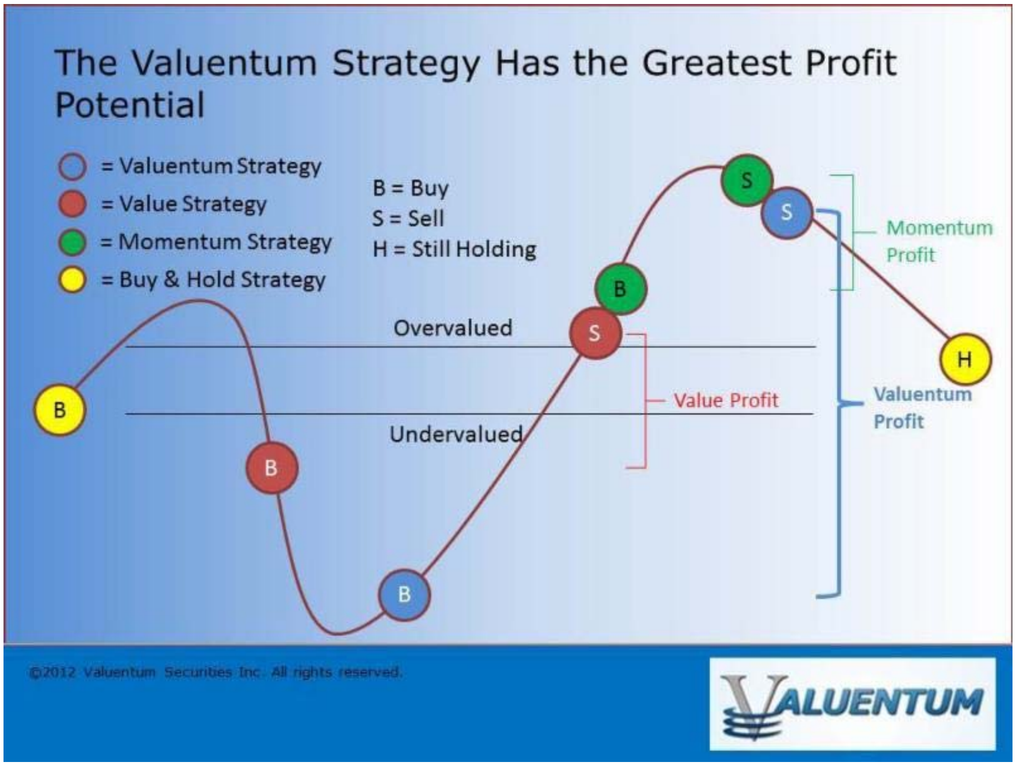
But why don't we churn our ideas by updating daily and trading a lot? Obviously, we don't think that's the secret to investment success. In quite the opposite approach, we strive to maximize profits on every idea that we pursue, with the understanding that momentum does exist and that prices over and under shoot intrinsic value all of the time. For example, as shown in the image above, a value strategy (10 --> 5) truncates potential profits, while a momentum strategy (4 --> 1) ignores profits generated via value assessments. At Valuentum, we're after the entire profit potential of each idea. So, for example, if a firm is added to the Best Ideas Newsletter portfolio as a 10 and is removed as a 5, we would have truncated profit potential by not letting it run to lower ratings. Most of our highly-rated Valuentum Buying Index rated stocks have generated the “outperformance” of the Best Ideas Newsletter portfolio, but these stocks' ratings declined over time as they were held (a good thing -- a declining VBI rating generally means the share price has advanced, assuming all else is well).

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### Not All Highly-Rated Stocks Are Added to the Newsletter Portfolios

Regarding the Valuentum process, as it is executed in the Best Ideas Newsletter portfolio, we do not “add” all stocks that register a 9 or 10, nor do we add the ones we do immediately thereafter. For example, Google (GOOG, GOOGL), now Alphabet, a current Best Ideas Newsletter portfolio “holding,” registered a 10 on the Valuentum Buying Index, but we remained patient and didn't “add” the company to our portfolio until after it reported earnings at the time, providing us with an even better entry point (as new information came to light). There are more "structural/timing" instances like the one with Alphabet, for example, that are extremely difficult to capture in any model, and understandably aren't as obvious to those outside looking in. Macro-economic, broader market valuation, and sector weighting considerations are other factors that impact the qualitative portfolio management process.

But why not add every highly-rated stock on the Valuentum Buying Index to the Best Ideas Newsletter portfolio? Think of it as if you were to imagine a value investor not adding and holding every undervalued stock to his/her portfolio. He or she wants the very best ones, in his or her opinion -- obviously, that means having to leave some good ideas behind. And then, of course, there are always tactical and sector weighting considerations in any portfolio construction, yet another reason why the human touch remains a vital aspect of the Valuentum process. At the core of how we use the VBI in the Best Ideas Newsletter portfolio, however, is a qualitative portfolio management overlay. The VBI rating helps to inform the process, but the Valuentum team makes the allocation decisions of the newsletter portfolio on the basis of a number of other firm-specific and portfolio criteria. Sometimes, under certain market conditions, we may even have to relax the VBI criteria entirely in order to do what we think is required to achieve newsletter portfolio goals.

**Some Examples of the Valuentum Buying Index In Action**

Okay, a couple examples. Take pre-split eBay (EBAY), which many years ago included PayPal (PYPL), as an example of our process in action. The stock initially flashed a rating of 10 in late September 2011, and we “added” it to the Best Ideas Newsletter portfolio. The VBI rating changed to a 6 in December 2011 and then back to a 10 in May 2012, but because the rating never breached a 1 or 2, we did not remove the position from the Best Ideas Newsletter portfolio. In the case of pre-split eBay, we sought to capture the entire pricing cycle and avoided truncating it as most pure value investors often do (and what we would had done, if we had removed the stock at that time). In many ways, pre-split eBay/PayPal has become one of the better examples to use for illustrating the prolonged outperformance driven by undervalued stocks that are beginning to generate good momentum. [We no longer include eBay in the newsletter portfolio, but its split-off PayPal is retained.]

There have been more straightforward opportunities in the Best Ideas Newsletter portfolio, too, especially in the case of EDAC Tech (EDAC), which tripled since it was added to the newsletter portfolio (never registering below a 9 along the way), and then of course, Apple (APPL), Visa (V) and Altria (MO), but it is usually through the nuances of the process that one truly comes to understand it (as in the eBay example). Not to be overlooked either, the Valuentum Buying Index rating also informs us when we may consider “removing” a position from the newsletter portfolios. Kinder Morgan (KMI), for example, registered a 1 on the Valuentum Buying Index just prior to its notorious fall and dividend cut. The VBI ratings on each stock's most recent 16-page report, downloadable directly from the website at www.valuentum.com, reflect our current opinion on the company.

In all, the Valuentum Buying Index rating system, as with all methodologies, helps to *inform* the investment decision process, but in constructing the newsletter portfolio, a qualitative overlay is not only necessary, in our view, but helps to optimize performance. If the returns of the Best Ideas Newsletter portfolio during the past 5+ years are any measure of the VBI rating system, it is performing fantastically well. Of course, please always contact your financial advisor to determine if any idea or strategy may be right for you.

(1) *"Why Valuentum Buying Index Ratings Matter"*
*https://www.valuentum.com/articles/20141003_1*

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